Spherical Transformer: Adapting Spherical Signal to Convolutional Networks

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Abstract

Convolutional neural networks (CNNs) have been widely used in various vision tasks, e.g. image classification, semantic segmentation, etc. Unfortunately, standard 2D CNNs are not well suited for spherical signals such as panorama images or spherical projections, as the sphere is an unstructured grid. In this paper, we present Spherical Transformer which can transform spherical signals into vectors that can be directly processed by standard CNNs such that many well-designed CNNs architectures can be reused across tasks and datasets by pretraining. To this end, the proposed method first uses locally structured sampling methods such as HEALPix to construct a transformer grid by using the information of spherical points and its adjacent points, and then transforms the spherical signals to the vectors through the grid. By building the Spherical Transformer module, we can use multiple CNN architectures directly. We evaluate our approach on the tasks of spherical MNIST recognition, 3D object classification and omnidirectional image semantic segmentation. For 3D object classification, we further propose a rendering-based projection method to improve the performance and a rotational-equivariant model to improve the anti-rotation ability. Experimental results on three tasks show that our approach achieves superior performance over state-of-the-art methods.

1 Introduction

Recently, with the increasing availability and popularity of omnidirectional sensors, a wide range of learning problems in computer vision and related areas requires processing signals in spherical domain. For instance, for omnidirectional images and 3D models, standard CNNs working with structured data are not perfectly applicable to them. This limitation is especially pronounced for 3D models, which provides accurate encoding of 3D objects. In recent years, various methods have been proposed to deal with 3D objects for different data representations, such as voxelization, point cloud, multi-view images and spherical image. Two very recent works [6, 8] propose different network architectures that achieve rotation invariance and direct operation in spherical domain. However, the sampling method in these networks is preliminary, which only maps spherical signals to local-distorted planar domains. This will result in undesirable distortions and lost of some information. The work [12] presents a new convolutional kernel to apply CNNs on unstructured grids, and overcomes the above shortcomings. However, it does not contain the standard convolutional operation which shows strong capabilities in 2D image classification and semantic segmentation tasks. Seeing the rich asset of existing CNNs modules e.g. VGG-11 [23] and U-Net [21] for traditional image data, we are motivated to devise a mechanism to bridge the mainstream standard CNNs to the spherical signal. One particular challenge is
how to express spherical signal in a structured manner.

Classic deep neural networks take structured vectors as input. How to encode the input vectors is crucial to the performance. Spatial Transformer Networks (STN) \[11\] are commonly used to learn spatial transformations on the input image to enhance the geometric invariance of the model. Inspired by STN, in this paper, we present a spherical transformer method to transform the spherical signals to structured vectors that can be processed by standard CNNs directly. As the proposed spherical transformer can be combined to multiple classic CNNs directly as a front-end module, it is able to deal with different tasks of spherical signals. In this paper, we focus on three typical applications: spherical MNIST recognition, 3D model classification and omnidirectional images semantic segmentation. In detail, we employ the popular VGG-11 \[23\] and U-Net \[21\] for 3D model classification and semantic segmentation separately. For MNIST recognition on sphere, we use a simple CNN with 5 layers to accomplish this task.

In summary, this paper makes the following contributions:

- We devise a spherical transformer module which can transform spherical signals into vectors friendly to standard CNNs. To our best knowledge, this is the first technique fulfilling such a transforming procedure from spherical data to structured data. One resulting advantage is that we can easily reuse the VGG-11 \[23\] and U-Net \[21\] architecture for spherical data. Moreover, our seamless use of standard CNNs enables the benefit of pretrain (transfer learning) across different datasets.

- We propose a novel rendering-based projection method which can project the local shading of the internal object points to the spherical image. This rendering method can enrich the spherical features and improve the classification performance of 3D object.

- Our spherical CNNs achieves superior performance on spherical MNIST recognition, 3D object classification and spherical image semantic segmentation, compared to state-of-the-art networks \[6,12\].

The rest of the paper is organized as follows. Section 2 discusses the related works which help the readers better understand the background of our approach. The approach for defocus blur detection by self-supervision and region based hard mining is presented in Section 3, whose promising performance is verified in the experiment part in Section 4. Section 5 concludes this paper.

2 Related Work

For the above tasks being addressed by the proposed approach, the existing deep learning methods could be divided into three categories: 3D-based, planar-image-based and spherical-image-based.

3D-based methods. 3D-based methods are mainly designated for voxel grids or point clouds as input data format. Like 2D images, voxels can be directly processed by using 3D convolution operations. However, due to memory and computational restrictions, the voxel-based methods are often limited to small voxel resolution. For instance, in VoxNet \[15\], the resolution of these occupancy grids is \(32 \times 32 \times 32\). Such a small resolution will result in the loss of many details. Although this issue has been recently alleviated by Octree-based representations such as OctNet \[20\], the cost of 3D CNNs is still distinctly higher than 2D neural networks of the same resolution.

Alternative approaches have been recently explored to handle 3D points. In this respect, the most famous work is PointNet \[17\]. It proposes a novel network architecture that operates on point clouds directly. Moreover, PointNet uses the global max pooling to solve the disorder of the input point cloud. However, PointNet cannot capture the local structure, which limits its ability to identify fine scenes and generalize complex scenes. PointNet++ \[18\] and DGCNN \[27\] alleviate this problem and achieve improved performance.

Planar-image-based methods. A key advantage of 3D based technology is that 3D objects can be accurately described by the corresponding 3D representations. However, the network architecture applying to 3D representations is (arguably) still in its open stage. As standard CNNs have achieved great success in the field of planar images, there exist methods using 3D object’s multi-view
images to classify the object. The two prevailing methods are MVCNN [24] and MVCNN-new [25]. They produce 12-view images of a 3D model and classify the rendered images through standard convolutional neural network architectures such as VGG [23], ResNet [10] which can be pretrained on ImageNet dataset. Although image-based technology can take advantage of the pre-trained parameters of classification networks and achieves very good results, object projection inevitably leads to information loss in theory.

For semantic segmentation, there have been recently proposed many methods, such as U-Net [21] and deeplab [4] etc. Nevertheless, these methods are all devised for 2D images. Converting a spherical panorama directly into a equirectangular image leads to severe distortion, especially near the pole, which makes these methods less effective.

Spherical-image-based methods. Several other works e.g. spherical CNNs [6] seek to combine 3D-based techniques and image-based techniques. In the work [1, 3], the authors provide benchmarks for semantic segmentation of 360 panorama images.

For 3D object classification, several classification networks based on spherical depth projection are proposed in recent years. [6] propose spherical convolutions that are rotational-equivariant. And spherical harmonic basis is used in [8] to obtain similar results. The above methods have achieved good results on 3D object classification through depth-based spherical projection. However, they often have restrictive applicability and can only be a specific task, largely due to the inflexibility of the adopted sampling method. More recently, convolution is achieved on unstructured grids by replacing the standard convolution with a differential operation [12]. While this kind of pseudo convolution lacks the ability to reuse standard CNNs. SFCNN [19] proposed a spherical fractal CNNs for point cloud analysis. It first projects the point cloud with extracting features onto the corresponding spherical points, and then uses the graph convolution for classification and object segmentation.

For equirectangular image segmentation, [26] proposed spherical convolution by changing the convolution kernel through equirectangular projection. SphereNet [7] introduces a framework for learning spherical image representations by encoding distortion invariance into con-

| Method           | Input         | Convolution feature               |
|------------------|---------------|-----------------------------------|
| Voxnet [15]      | voxels        | 3D CNNs                           |
| OctNet [20]      |               |                                   |
| PointNet [17]    | points        | MLP implemented by 1 × 1 conv kernel |
| PointNet++ [18]  |               |                                   |
| DGCNN [27]       |               |                                   |
| SFCNN [19]       |               |                                   |
| MVCNN [24]       | images        | 2D CNNs                           |
| MVCNN-NEW [25]   |               |                                   |
| S2CNN [6]        | spherical     | FFT of spherical non-uniform points |
| SphericalCNN [8] | spherical     |                                   |
| UGSCNN [12]      | spherical     | parameterized differential operators to replace 2D conv |
| DeepSphere [16]  | spherical     | GNNs implemented by 1 × 1 conv kernel |
| STM (Ours)       | spherical     | 2D CNNs                           |

Table 1: Features of 3D object recognition networks.
volutional filters. But this method only supports \(3 \times 3\) convolution kernel and max pool, and it needs bilinear interpolation to index the adjacent points of spherical points while we are looking for them directly.

In recent studies, DeepSphere\(^{[16]}\) proposed a spherical CNNs by using graph neural networks for cosmological data analysis. Table 1 briefly summaries the convolution characteristics of common 3D object recognition networks.

### 3 The Proposed Approach

This section shows our spherical transformer module. The spherical point uniform sampling method is described, followed by the depiction of spherical transformer and how to combine it with sampling method to construct spherical convolution and spherical pooling layer. Finally, the details of our 3D object classification network and spherical semantic segmentation network are presented.

#### 3.1 Spherical sampling

The major concern for processing spherical signals is distortion introduced by projecting signals on other formats such as projecting panorama image to planar image. Thus the best way to process spherical signals is finding a spherical uniform sampling method. We found HEALPix spherical grid\(^{[9]}\) (as shown in Fig. 1) and icosahedral spherical grid\(^{[2]}\) methods are able to achieve this goal. Here we adopt HEALPix sampling in the proposed method, mainly because most spherical points on HEALPix grid have 8 neighbors. It can form \(3 \times 3\) transformer grid and then convert to vectors to be processed by \(3 \times 3\) convolution kernels. But for icosahedral grid, all spherical points have 6 neighbors, which means they can only be processed by \(1 \times 7\) convolution kernels.

HEALPix grid starts with 12 points as the level-0 resolution. Each progressive resolution is one level above the previous with 4 times the number of points. Hence, the number of sampling points on the sphere \(n_p^l\) with level-\(l\) is:

\[
n_p^l = 12 \cdot 4^l
\]

It can be clearly found that the resolution changing process perfectly matches the \(2 \times 2\) pooling layer.

#### 3.2 Spherical transformer module

Sphere is locally planar and a few of spherical grids in local region are structured, such as HEALPix spherical grid\(^{[9]}\) as adopted in the paper. Thus the next key step is to conduct a transformer grid by using the location information of spherical points and their neighbors. Specifically, our proposed spherical transformer module (STM) include two layers: spherical convolution layer and spherical pooling layer, as will be described in detail.

**Spherical convolution layer.** Standard convolution layer need structured grid such as image data. As shown in Fig. 1, the local points is structured in HEALPix spherical grid. It can be seen that most of the spherical points have eight adjacent points, one of which is depicted with green in Fig. 1. For level-\(l\) (\(l \geq 1\)), there are always 24 points of which the number of the adjacent points is 7. For specific examples, see the blue part of Fig. 1. For every point on HEALPix grid, the spherical convolution operation includes the following steps, as shown in Fig. 1 for level-3 HEALPix grid:

1) **Determining the point index and extracting the corresponding feature vectors.** Here we adopt the nested scheme which arranges the point index hierarchically (see\(^{[9]}\) for detail). 768 points in level-3 HEALPix grid are arranged from small to large as the first row of Fig. 1 whose element is the feature vector of the current index point.

2) **Building the spherical transformer grid of convolution beforehand.** As the HEALPix grid point index are preassigned, the indexes of the adjacent points for every point is known. Thus we can generate the \(3 \times 3\) transformer grid for every point. For some points with only 7 adjacent points, the grid value of the missing position is set to be -1. The second row of Fig. 1 shows some examples.

3) **Obtaining the transformed vectors for convolution.** This transform operation is very similar to the Spatial Transformer Network (STN)\(^{[11]}\). For every vector in step 1), we construct its \(3 \times 3\) neighbor vectors according to the transformer grid defined in step 2). For the points with only 7 adjacent points, the missing vector is set to be 0. See the third row of Fig. 1 for illustration.

4) **Running the standard \(3 \times 3\) convolution.** Since the transformed vectors has been obtained in the above
step, we can use standard $3 \times 3$, stride $1 \times 3$ convolution kernels to process it directly. For example, for the feature vectors $U \in \mathbb{R}^{1 \times 768 \times C_1}$ in level-3, it is transformed to the vectors $V \in \mathbb{R}^{1 \times 768 \times C_2}$ after the processing of $\text{conv}3 \times 3(C_1, C_2)$ with stride $1 \times 3$.

Thus we can use $1 \times 4$ max pooling layer directly instead of build spherical transformer grid for spherical pooling layer. Consequently, the spherical features in level-$l$ is straightforward pooled to the features in level-$l-1$ as they are coded in proper order in HEALPix grid.

### 3.3 Network architecture

As described in Fig. 1, we have constructed our spherical convolution layer and spherical pooling layer by using the proposed spherical transformer method. By doing this, we can directly use the classical CNN architectures as we originally designed. For 3D object classification, we adopt VGG-11 network architecture but replace its convolution layer and pooling layer with our pro...
posed spherical convolution and pooling layer. And to get rotational-equivariant, we changed the basic VGG-11 model and more details were described in next section. For semantic segmentation, we similarly construct a novel network which combines the U-Net architecture with the proposed STM. Detailed schematic for these two architectures is shown in Fig. 2. Moreover, both the classification and segmentation networks share a common encoder architecture. Since these architectures have been verified in various vision tasks, it is reasonable to apply them to the proposed spherical structured grids.

Anti-rotation model As previous studies e.g. S2CNN [6] and SphericalCNN [8] propose spherical convolutions that are rotational-equivariant, so to improve the anti-rotation ability of our 3D object classification model, we modify our VGG-11 liked model architecture as shown in Fig. 2. It is well known that convolutional neural networks implement translation-equivariant by construction, for other transformations such as rotations, however, they are ineffective. Though recently some convolution kernels are proposed for rotation-equivariant such as G-CNNs [5] and SFCNNs [28], here we resort to the simple $1 \times 1$ convolution kernel which is naturally rotation-equivariant. For its simplicity, we add $1 \times 1$ convolution kernel to our basic model. To find features that are sensitive to these two convolutions, for every $3 \times 3$ convolution layer before max pooling, we sum these two features. Certainly, to preserve most rotation-equivariant features, we concatenate these two features before the first fully-connected layer. More details can be seen in Fig. 2.

4 Experiments

We first use the spherical MNIST experiment to prove the effectiveness of our method on reusing the standard 2D CNNs, leading to fewer parameters while better results compared with peer methods as shown in Table 2. Then we evaluate the proposed approach in two important applications: 3D object classification and spherical image semantic segmentation.

4.1 Spherical MNIST

To verify its efficiency, we first use our method to solve the classic digital recognition problem.
| Method       | Acc (%) | Parameter # |
|--------------|---------|-------------|
| S2CNN [6]    | 96.00   | 58k         |
| UGSCNN [12]  | 99.23   | 62k         |
| STM (Ours)   | 99.36   | 32k         |

Table 2: Classification accuracy on the spherical MNIST dataset for validating the proposed STM.

**Experiment setup.** To project digits onto the surface of the sphere, we follow the projection method of S2CNN [6] and UGSCNN [12]. We benchmark our method with the above two spherical CNNs. All models are trained and tested on data that has not been rotated. In this experiment, we use a 5 layers CNN architecture with 4 conv-pool-BN-ReLU and 1 FC-softmax.

**Results and discussion.** Table 2 shows the classification accuracy on spherical MNIST. It shows that our method outperforms S2CNN and UGSCNN. In particular, the number of parameters of our model is about only half of that of the above models. We attribute our success to the seamless reuse of 2D CNNs which has been dominant in wide range of vision tasks.

### 4.2 3D object classification

The benchmark dataset used in this task is ModelNet40 [29]. It contains 12,311 shapes across 40 categories, which is used to illustrate the applicability of our approach in 3D deep learning. For this study, we focus on classification accuracy and rotational-equivariant. Two types of spherical projection in our experiments are used: depth-based projection and rendering-based projection.

**Depth-based projection.** For depth-based projection, we follow the processing protocol of [6]. Specifically, as shown in Fig. 3, we first move the model to the origin and then normalize it. Then we calculate level-5 resolution spherical points and send a ray towards the origin for each point. Three kinds of information from the intersection are obtained: ray length, sin and cos values of the angle between the surface normal of the intersected object point and the ray. The data is further augmented by using the convex hull of the input model, finally forming spherical signals with 6 input channels. The rightmost plot in Fig. 3 shows the visualized depth-based spherical signals. Even if spherical image is one kind of feature representation from 3D to 2D, we can clearly see the various parts of the table, just like a distorted image.

**Rendering-based projection.** Motivated by the multi-view based method [13] that has achieved the best performance on ModelNet40 dataset, we explore and propose a rendering-based spherical projection method. However, such rendering-based methods have difficulty in stitching multi-view images to a spherical image directly. This is because the projections of multi-view images on spherical image are not aligned. One 3D object point can even appear multiple times in stitched spherical image. Therefore, we propose a novel projection strategy to separately obtain projections of 12 regions whose inner points correspond to different parts of the object, while boundary points correspond to the same part. For example, in Fig. 3 the red and green regions are 2 of 12 regions divided by HEALPix grid, respectively. We put the virtual camera on the ray of the origin and the center of this region which captures the image of the model from the current perspective. By adding six fixed point light sources on +x, -y, +z axes, 12 gray images can be rendered. Through the depth-based projections, we already know the point at which the model intersects the spherical ray. Hence, the gray value of one spherical point can be obtained by re-projecting the corresponding object point back to the rendered image of each region. It can be found that our rendering-based method only uses the internal points of the object, which contains the local shading of the object surface, without contour information. The third sub-figure from left to right in Fig. 3 shows the rendering-based spherical images from the view of the camera of the green region. Although the rendering spherical image is not visually straightforward, it indeed provides alternative feature that improves the performance.

**Experiment setup.** For this task, the level-5 spherical resolution is used. We use two spherical inputs to train the network separately. For classification accuracy, we use the aligned ModelNet40 data [22]. While SO(3)/SO(3) means trained and tested with arbitrary rotations. Our
rendering-based projection method can use the VGG-11 model parameters pre-trained on the ImageNet data. For classification accuracy, we compare the best result of our method with other 3D deep learning methods. The baseline algorithms we choose include UGSCNN [12], PointNet++ [18], VoxNet [15], S2CNN [6], SphericalCNN [8], SFCNN [19] and MVCNN [24].

Results and discussion. Table 3 shows the classification accuracy on ModelNet40. The proposed spherical depth feature based model is superior to the above existing methods. And our rotational-equivariant model shows better performance in both the best classification accuracy and SO(3)/SO(3) classification accuracy. Our rendering-based approach also achieves promising results after using pre-training parameters. The overall model means we combine the features of the penultimate full-connection.
layer of the two methods and retraining the last full-connection layer. When combining depth-based projection and rendering-based projection, our overall method achieves the highest accuracy. This also suggests that our devised render-based projection is effective and complementary to depth-based projection method.

4.3 Spherical image semantic segmentation

We demonstrate the semantic segmentation capability of the proposed spherical transformer module on the spherical image semantic segmentation task. We use the Stanford 2D3DS dataset [1] for comparison with the state-of-the-art UGSCNN [12]. The 2D3DS dataset contains a total of 1,413 equirectangular RGB images, along with their corresponding depths, and semantic annotations across 13 different classes. Except compared with UGSCNN aimed to segment spherical image, we also include classic 2D image semantic segmentation networks for more comprehensive comparison.

Experiment setup. To apply our method on semantic segmentation tasks, the first thing is sampling on the original rectangular images to obtain spherical signals. To make a fair comparison with UGSCNN [12], we follow the interpolation method of UGSCNN. The input RGB-D channels are interpolated using bilinear interpolation, while semantic segmentation labels are acquired using nearest-neighbor interpolation. We use level-5 resolution and the official 3-fold cross validation to train and evaluate the experimental results. For this task, we benchmark our semantic segmentation results against the spherical semantic segmentation architecture UGSCNN and two classic semantic segmentation networks: U-Net [21] and FCN8s [14]. We evaluate the performance under two standard metrics: mean Intersection-over-Union (mIoU), and pixel-accuracy. The methods are compared under two settings: peak performance and parameter efficiency study by varying model parameters. For parameter efficiency study, we change the number of parameters by reducing the dimension of the convolution layer. The only difference between our network and the standard U-Net is the dimension of the last layer of our model encoder is 512, rather than 1024, as the ladder case does not have obvious improvement.

Results and discussion. Figure 5 compares our model performance against state-of-the-art baselines. Our spherical segmentation network significantly outperforms UGSCNN and two planar baselines over the whole parameter range. Here three different parameter numbers for each method denote the reduction of feature dimensionality, in line with the setting in UGSCNN. Fig. 4 shows a visualization of our semantic segmentation results compared to the ground truth, UGSCNN and two planar baselines. It can be seen that our method clearly achieves the best accuracy and the results are also visual appealing.

5 Conclusion and Outlook

In this paper, we have presented a novel method to transform the spherical signals to structured vectors that can be processed through standard CNNs directly. By utilizing the proposed STM, the convolution operation on the spherical signals is easily implemented as on 2D planar image. Thus it is feasible to deal with spherical signals using various mature CNN architectures. Experimental results show significant improvements upon a variety of strong baselines in both tasks for 3D object classification and spherical image semantic segmentation.

With the increasing availability and popularity of omnidirectional sensors such as 3D or LIDAR panorama sensors in both the consumer market and industry, we believe that the demand for specialized models for spherical signals will increase in the near future. Compared with the previous methods, the proposed STM is intuitive and direct to spherical signals. Therefore, the shown classification and segmentation results can be achieved by simply adjusting the common 2D CNNs without fine-tuning the network architecture and parameters. In the future, we will adapt our STM module to more vision tasks, such as shape alignment, optical flow and scene flow estimation.

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Figure 4: Semantic segmentation results on Stanford 2D3DS test dataset. Our results are generated on a level-5 HEALPix grid and mapped to the planar image by using nearest neighbor sampling for visualization. Each row shows the results of different methods including ground truth for a specific scene. Note only our method well captures the beam structure.

Figure 5: Parameter efficiency study on 2D3DS for semantic segmentation. Our spherical segmentation model outperforms UGSCNN and two planar-based methods by notable margin across all parameter regimes.

References

[1] I. Armeni, A. Sax, A. R. Zamir, and S. Savarese. Joint 2D-3D-Semantic Data for Indoor Scene Understanding. ArXiv e-prints, Feb. 2017.
[2] J. R. Baumgardner and P. O. Frederickson. Icosahedral Discretization of the Two-Sphere. SIAM Journal on Numerical Analysis, 22:1107–1115, Dec. 1985.
[3] Angel Chang, Angela Dai, Thomas Funkhouser, Maciej Halber, Matthias Niessner, Manolis Savva, Shuran Song, Andy Zeng, and Yinda Zhang. Matterport3d: Learning from rgb-d data in indoor environments. arXiv preprint arXiv:1709.06158, 2017.
[4] Liang-Chieh Chen, George Papandreou, Iasonas Kokkinos, Kevin Murphy, and Alan Loddon Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully...
connected crfs. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40:834–848, 2018.

[5] Taco Cohen and Max Welling. Group equivariant convolutional networks. In International conference on machine learning, pages 2990–2999, 2016.

[6] Taco S. Cohen, Mario Geiger, Jonas Köhler, and Max Welling. Spherical CNNs. In International Conference on Learning Representations, 2018.

[7] Benjamin Coors, Alexandru Paul Condurache, and Andreas Geiger. Spherenet: Learning spherical representations for detection and classification in omnidirectional images. In Proceedings of the European Conference on Computer Vision (ECCV), pages 518–533, 2018.

[8] Carlos Esteves, Christine Allen-Blanchette, Ameesh Makadia, and Kostas Daniilidis. Learning so(3) equivariant representations with spherical cnns. In Vittorio Ferrari, Martial Hebert, Cristian Sminchisescu, and Yair Weiss, editors, Computer Vision – ECCV 2018, pages 54–70, Cham, 2018. Springer International Publishing.

[9] K. M. Gorski, Eric Hivon, A. J. Banday, B. D. Wandelt, F. K. Hansen, M. Reinecke, and M. Bartelmann. HEALPix - A Framework for high resolution discretization, and fast analysis of data distributed on the sphere. Astrophys. J., 622:759–771, 2005.

[10] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 770–778, 2016.

[11] Max Jaderberg, Karen Simonyan, Andrew Zisserman, et al. Spatial transformer networks. In Advances in neural information processing systems, pages 2017–2025, 2015.

[12] Chiyu Max Jiang, Jingwei Huang, Karthik Kashinath, Prabhat, Philip Marcus, and Matthias Niessner. Spherical CNNs on unstructured grids. In International Conference on Learning Representations, 2019.

[13] Asako Kanezaki, Yasuuki Matsushita, and Yoshifumi Nishida. Rotationnet: Joint object categorization and pose estimation using multiviews from unsupervised viewpoints. 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5010–5019, 2018.

[14] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3431–3440, 2015.

[15] Daniel Maturana and Sebastian Scherer. Voxnet: A 3d convolutional neural network for real-time object recognition. In 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pages 922–928. IEEE, 2015.

[16] Nathanaël Perraudin, Michaël Defferrard, Tomasz Kacprzak, and Raphaël Sgier. Deepsphere: Efficient spherical convolutional neural network with healpix sampling for cosmological applications. Astronomy and Computing, 27:130–146, 2019.

[17] Charles R Qi, Hao Su, Kaichun Mo, and Leonidas J Guibas. Pointnet: Deep learning on point sets for 3d classification and segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 652–660, 2017.

[18] Charles Ruizhongtai Qi, Li Yi, Hao Su, and Leonidas J Guibas. Pointnet++: Deep hierarchical feature learning on point sets in a metric space. In Advances in Neural Information Processing Systems, pages 5099–5108, 2017.

[19] Yongming Rao, Jiwen Lu, and Jie Zhou. Spherical fractal convolutional neural networks for point cloud recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 452–460, 2019.

[20] Gernot Riegler, Ali Osman Ulusoy, and Andreas Geiger. Octnet: Learning deep 3d representations at high resolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017.

[21] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention, pages 234–241. Springer, 2015.
[22] Nima Sedaghat, Mohammadreza Zolfaghari, Ehsan Amiri, and Thomas Brox. Orientation-boosted voxel nets for 3d object recognition. arXiv preprint arXiv:1604.03351, 2016.

[23] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014.

[24] Hang Su, Subhransu Maji, Evangelos Kalogerakis, and Erik G. Learned-Miller. Multi-view convolutional neural networks for 3d shape recognition. In Proc. ICCV, 2015.

[25] Jong-Chyi Su, Matheus Gadelha, Rui Wang, and Subhransu Maji. A deeper look at 3d shape classifiers. In ECCV Workshops, 2018.

[26] Yu-Chuan Su and Kristen Grauman. Learning spherical convolution for fast features from 360 imagery. In Advances in Neural Information Processing Systems, pages 529–539, 2017.

[27] Yue Wang, Yongbin Sun, Ziwei Liu, Sanjay E Sarma, Michael M Bronstein, and Justin M Solomon. Dynamic graph cnn for learning on point clouds. arXiv preprint arXiv:1801.07829, 2018.

[28] Maurice Weiler, Fred A Hamprecht, and Martin Storath. Learning steerable filters for rotation equivariant cnns. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 849–858, 2018.

[29] Zhirong Wu, Shuran Song, Aditya Khosla, Fisher Yu, Linguang Zhang, Xiaoou Tang, and Jianxiong Xiao. 3d shapenets: A deep representation for volumetric shapes. 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 1912–1920, 2015.