

MVImgNet: A Large-scale Dataset of Multi-view Images

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Figure 1. It is time to embrace MVImgNet! We introduce MVImgnet, a large-scale dataset of *multi-view images*, which is efficiently collected by shooting videos of real-world objects. It enjoys 3D-aware signals from multi-view consistency, being a soft bridge between 2D and 3D vision. Through dense reconstruction on MVImgNet, we also present a large-scale real-world 3D object *point cloud* dataset – MVPNet. **Exterior:** Examples of various multi-view images in MVImgNet (see Fig. 3 more intuitively). **Interior:** Instances of colorful point clouds from MVPNet (see Fig. 7 more clearly) are assembled into a stereo sign of ‘MVImgNet’.

Abstract

Being data-driven is one of the most iconic properties of deep learning algorithms. The birth of ImageNet [24] drives a remarkable trend of ‘learning from large-scale data’ in computer vision. Pretraining on ImageNet to obtain rich universal representations has been manifested to benefit various 2D visual tasks, and becomes a standard in 2D vision. However, due to the laborious collection of real-world 3D data, there is yet no generic dataset serving as a counterpart of ImageNet in 3D vision, thus how such a dataset can impact the 3D community is unraveled. To remedy this defect, we introduce MVImgNet, a large-scale dataset of multi-view images, which is highly convenient to gain by shooting videos of real-world objects in human daily life. It contains 6.5 million frames from 219,188 videos crossing objects from 238 classes, with rich annotations of object masks, camera parameters, and point clouds.

The multi-view attribute endows our dataset with 3D-aware signals, making it a soft bridge between 2D and 3D vision.

We conduct pilot studies for probing the potential of MVImgNet on a variety of 3D and 2D visual tasks, including radiance field reconstruction, multi-view stereo, and view-consistent image understanding, where MVImgNet demonstrates promising performance, remaining lots of possibilities for future explorations.

Besides, via dense reconstruction on MVImgNet, a 3D object point cloud dataset is derived, called MVPNet, covering 87,200 samples from 150 categories, with the class label on each point cloud. Experiments show that MVPNet can benefit the real-world 3D object classification while posing new challenges to point cloud understanding.

MVImgNet and MVPNet will be public, hoping to inspire the broader vision community.

1. Introduction

Being data-driven, also known as data-hungry, is one of the most important attributes of deep learning algorithms. By training on large-scale datasets, deep neural networks are able to extract rich representations. In the past few years, the computer vision community has witnessed the bloom of such ‘*learning from data*’ regime [43, 44, 55], after the birth of ImageNet [24] – the pioneer of large-scale real-world image datasets. Notably, pretraining on ImageNet is well-proven to boost the model performance when transferring the pretrained weights into not only high-level [34, 41, 42, 60, 61] but also low-level visual tasks [15, 57], and becomes a *de-facto* standard in 2D. Recently, various 3D datasets [5, 9, 11, 23, 33, 96, 104] are produced to facilitate 3D visual applications.

However, due to the non-trivial scanning and laborious labeling of real-world 3D data (commonly organized in point clouds or meshes), existing 3D datasets are either synthetic or their scales are not comparable with ImageNet [24]. Consequently, unlike in 2D vision where models are usually pretrained on ImageNet to gain universal representation or commonsense knowledge, most of the current methods in 3D area are directly trained and evaluated on particular datasets for solving specific 3D visual tasks (*e.g.*, NeRF dataset [64] and ShapeNet [11] for novel view synthesis, ModelNet [96] and ScanObjectNN [88] for object classification, KITTI [33] and ScanNet [23] for scene understanding). Here, two crucial and successive issues can be induced: **(1)** *There is still no generic dataset in 3D vision, as a counterpart of ImageNet in 2D.* **(2)** *What benefit such a dataset can endow to 3D community is yet unknown.* In this paper, we focus on investigating these two problems and set two corresponding targets: Build the primary dataset, then explore its effect through experiments.

Milestone 1 – Dataset:

For a clearer picture of the first goal, we start by carefully revisiting existing 3D datasets as well as ImageNet [24]. **i)** 3D synthetic datasets [11, 96] provide rich 3D CAD models. However, they lack *real-world* cues (*e.g.*, context, occlusions, noises), which are indispensable for model robustness in practical applications. ScanObjectNN [88] extracts real-world 3D objects from indoor scene data, but is limited in scale. For 3D scene-level dataset [5, 10, 23, 33, 37, 81], their scales are still constrained by the laborious scanning and labeling (*e.g.*, millions of points per scene). Additionally, they contain specific inner-domain knowledge such as a particularly intricate indoor room or outdoor driving configurations, making it hard for general transfer learning. **ii)** Although ImageNet [24] contains the most comprehensive real-world objects, it only describes a 2D world that misses *3D-aware* signals. Since humans live in a 3D world, 3D consciousness is vitally important for realizing human-like intelligence and solving real-life visual problems.

Based on the above review, our dataset is created from a new insight – **multi-view images**, as a soft bridge between 2D and 3D. It lies several benefits to remedying the aforementioned defects. Such data can be *easily gained* in *considerable sizes* via shooting an object around different views on common mobile devices with cameras (*e.g.*, smartphones), which can be collected by crowd-sourcing in *real world*. Moreover, the multi-view constraint can bring natural 3D visual signals (later experiments show that this not only benefits 3D tasks but also 2D image understanding). To this end, we build **MVImgNet**, containing **6.5** million frames from **219,188** videos crossing real-life objects from **238** classes, with rich annotations of object masks, camera parameters, and point clouds. You may take a glance at our MVImgNet from Fig. 1.

Milestone 2 – Experimental Exploration:

Now facing the second goal of this paper, we attempt to probe the power of our dataset by conducting some pilot experiments. Leveraging the multi-view nature of the data, we start by focusing on the view-based 3D reconstruction task and demonstrate that pretraining on MVImgNet can not only benefit the *generalization ability of NeRF* (Sec. 4.1), but also *data-efficient multi-view stereo* (Sec. 4.2). Moreover, for image understanding, although humans can easily recognize one object from different viewpoints, deep learning models can hardly do that robustly [26, 38]. Considering MVImgNet provides numerous images of a particular object from different viewpoints, we verify that MVImgNet-pretrained models are endowed with decent *view consistency* in general *image classification* (supervised learning in Sec. 5.1, self-supervised contrastive learning in Sec. 5.2) and *salient object detection* (Sec. 5.3).

Bonus – A New 3D Point Cloud Dataset – MVPNet:

Through dense reconstruction on MVImgNet, a new 3D object **point cloud dataset** is derived, called **MVPNet**, which contains **87,200** point clouds with 150 categories, with the class label on each point cloud (see Fig. 7). Experiments show that MVPNet not only benefits the real-world 3D object classification task but also poses new challenges and prospects to point cloud understanding (Sec. 6).

MVImgNet and MVPNet will be public, hoping to inspire the broader vision community.

2. Related Work

Single-view image datasets. The MNIST database [1] is one of the most pioneering datasets, composed of 70k monochrome images of handwritten digits. The CIFAR10 and CIFAR100 datasets proposed by [54], respectively collect 60k tiny color images (32×32) of various common objects or animals in 10 and 100 classes. ImageNet [24] is presented with a large scale, high accuracy, large diversity, and hierarchical structure, which provides opportunities for training deep neural networks. In detection

and segmentation tasks, MSCOCO [58] is one of the most popular datasets containing 328k images with rich annotations. Some other datasets include PASCAL VOC [28], Visual Genome [53], Cityscapes [22], MPII [4], *etc.* Although these datasets facilitate the development of deep visual learning, they mainly serve for 2D single-view image understanding, which limits their applications in 3D vision.

Video datasets. Another line is video datasets. Pioneering works construct the HMDB-51 [56] and UCF-101 [82] dataset. Afterward, the ActivityNet [8] and Kinetics [49] datasets are constructed of a larger scale and variation, of which the latter has collected 650k video clips that cover 700 classes. Besides, some datasets are built for human pose estimation [48, 90] and object detection/segmentation/tracking [69, 95, 112]. IEMOCAP [7] provides video data for the task of multimodal emotion recognition. MSVD [14] and MSR-VTT [103] annotate videos with extra captions. Further, HowTo100M [63] proposes a larger-scale one of 136 million samples from narrated instructional videos. ActivityNet Captions [52] introduces the task of dense-captioning events and constructs a dataset with 20k videos. These datasets are primarily for video understanding which is different from our objective.

3D datasets. As the applications in 3D vision attract increasing attention, various 3D datasets are proposed. One line of works focuses on indoor scenes [5, 10, 23, 47, 78, 81, 100], where S3DIS [5] and ScanNet [23] are two of most popular datasets. In addition, some works provide 3D object point clouds for contextual object surface reconstruction [6, 29]. 3D outdoor scenes are scanned via LiDAR sensors [9, 33, 37, 83] for autonomous driving. ShapeNet [11] and ModelNet [96] are two object-centric datasets that provide rich 3D Computer-Aided Design (CAD) models for shape analysis, followed by similar datasets [51, 98], which are usually low-quality, untextured, and have a domain gap with real-world objects. Another line of works [20, 21, 68, 79, 89, 104] advocate real 3D objects but are still limited in scale. We close this gap by shooting multi-view images of real-world objects, which capture the 3D awareness while allowing a scalable collection.

Multi-view image datasets. Multi-view image data is recently regarded as the source of 3D reconstruction or novel view synthesis. Early works collect multi-view images of real objects but only provide 3D models that are approximated [99] or for only a few instances [20]. Henzler *et al.* [45] contribute a larger video dataset to benchmark the task of 3D reconstruction. Another concurrent dataset, Objectron [3], annotates 3D bounding boxes and ground planes for all objects but lacks camera poses or point clouds for all 15k videos. GSO [27] gets clean 3D models with textures via scanning common household items but includes only a limited number of samples. Some works also construct synthetic multi-view datasets [11, 32, 86, 101, 108]. Neverthe-

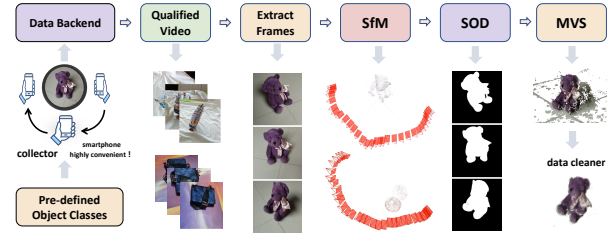


Figure 2. The efficient data acquisition pipeline of MVImgNet.

less, these datasets have a small scale and category range for special tasks, which limits the robust and generic learning of 3D deep models. We construct a large-scale multi-view image dataset – MVImgNet, which contains 219k videos for real-world objects in a wide range of 238 categories.

Special discussions on CO3D [74]. Very recently, CO3D extends [45] to 19k videos covering 50 object categories. Although we share a similar idea in the light of object-centric multi-view data collections, our MVImgNet enjoys conspicuously larger scales.

More importantly, we have fundamentally different *motivations* and *insights*. The primary motivation of CO3D is *exactly pre-set*, which is to transfer the 3D reconstruction training/evaluation from synthetic datasets into the real-world setup. In contrast, MVImgNet examines existing 3D datasets by re-walking the past development journey in the 2D domain. Concretely, through reflecting on how ImageNet [24] demonstrates its generic impact on data-hungry algorithms, we attempt to build a 3D counterpart of ImageNet and choose multi-view images as a soft bridge between 2D and 3D. Instead of nailing down a special target, we conduct a variety of *pilot* studies on how MVImgNet can benefit miscellaneous visual tasks, aiming to inspire and retain lots of possibilities for the broader vision community.

In the later experiments, our datasets indeed show greater power than CO3D on different visual challenges.

3. The Basis – MVImgNet Dataset

As shown in Fig. 2, the whole data acquisition pipeline of MVImgNet is highly efficient, which is illustrated below.

3.1. Raw Data Preparation

Building a large-scale dataset is always challenging, due to not only the laborious data collection but also the non-trivial annotation, which is especially critical for real-world 3D data [5, 10, 23]. Thanks to the rapid development of mobile devices, shooting a video around an object in the wild becomes highly convenient and accessible in our daily life, which makes multi-view images be easily gained by crowd-sourcing.

Composition setup. We set up some constraints on the ratio. Depending on the category, each class is initially set with the different expected number of video cap-

| Annotation | Collected | Valid | GPU hours |
|--------------|-----------|---------|-----------|
| Sparse | 219,188 | 215,755 | 3,806.8 |
| Segmentation | 104,261 | \ | 2,316.9 |
| Dense | 98,899 | 87,200 | 25,122.4 |

Table 1. **Data statistics**, including **collected** amount, **valid** amount after cleaning, and the **GPU hours** for processing.

| Dataset | Real | # of objects | # of categories | Multi-view | 3D-GT |
|----------------------------|------|--------------|-----------------|---------------|--------------|
| ShapeNet [11] | × | 51k | 55 | render | CAD model |
| ModelNet [96] | × | 12k | 40 | render | CAD model |
| Choi <i>et al.</i> [20] | ✓ | 2k | 9 | 360° captured | RGB-D scan |
| Objectron [3] | ✓ | 15k | 9 | limited | 3D bbox, pcl |
| GoogleScan [27] | ✓ | 2k | NA | 360° captured | RGB-D scan |
| Henzler <i>et al.</i> [45] | ✓ | 2k | 7 | 360° captured | pcl |
| ScanObjectNN [88] | ✓ | 14k | 15 | limited | pcl |
| CO3D [74] | ✓ | 19k | 50 | 360° captured | - |
| CO3D-pcl [74] | ✓ | 5k | 50 | 360° captured | pcl |
| MVImgNet (ours) | ✓ | 220k | 238 | 180° captured | - |
| MVPNet (ours) | ✓ | 87k | 150 | 180° captured | pcl |

Table 2. **Comparison** between our datasets and related ones. “pcl” denotes point clouds, “bbox” means bounding boxes.

tures regarding their *generality*, *e.g.*, the number of captures for “bottles”, “bags” and “snacks” is planned to be around 2000, while the number of “chips”, “apples” and “guitars” is set to about 1000. This setting is closer to real life.

Video capture. How to capture videos directly affect the quality of our data, so we draw up the following requirements as guidance for the captured videos: 1) The length of each video should be about 10 seconds. 2) The frames in the video should not be blurred. 3) Each video should capture 180° or 360° view of the object as much as possible. 4) The proportion of the object in the video should be above 15%. 5) Each video can only contain one class of principal object. 6) The captured object should be stereoscopic.

Crowdsourcing. We employ around 1000 normal collectors from different professions (*e.g.*, teacher, doctor, student, cook, babysitter) and ages (20~50). Each of them is asked to take several videos in their daily life, (*i.e.*, denoting diverse real-world environments) and upload them to the backend. Meanwhile, about 200 new well-trained expert data cleaners are responsible to review each submission and assure it fulfills the aforementioned capture requirements, when they may report some feedback or directly delete the unqualified submissions. The whole procedure ensures both the *diversity* and *quality* of the raw videos.

3.2. Data Processing

For each qualified video submission, we exploit an automatic process to obtain the common 2D and 3D annotations, including object masks, camera intrinsic and extrinsic, depth maps, and point clouds.

Sparse reconstruction. Following the procedure of [64, 65], the sparse reconstruction aims to reconstruct the camera intrinsic and extrinsic for each video, by applying the COLMAP Structure-from-Motion (SfM) algorithm [75] on a series of equal-time-interval chosen frames.



Figure 3. Some **frames** sampled from MVImgNet.

Foreground object segmentation. Each frame extracted from the original video is fed to the CarveKit [70] for generating the binary foreground object mask, not only benefiting the dense reconstruction but also contributing to the further step of salient object detection (Sec. 5.3).

Dense reconstruction. With the sparse model output from COLMAP SfM, we employ multi-view stereo [76] of COLMAP to generate the dense depth and normal maps for each frame. We extract the depths of an object using the binary foreground masks, which are then back-projected and fused according to the normal information, yielding a densely reconstructed point cloud for each video. Finally, the point cloud is manually cleaned by: 1) Delete the object with obvious noisy or extremely sparse reconstruction. 2) Remove all backgrounds. The final derived 3D point cloud dataset – MVPNet, is illustrated in Sec. 6.1.

3.3. Dataset Summary

Statistics. The statistics of MVImgNet are shown in Tab. 1, and Tab. 2 compares our datasets with other alternatives. MVImgNet includes 238 object classes, from 6.5 million frames of 219,188 videos. Fig. 3 shows some samples of MVImgNet. The annotation comprehensively covers object masks, camera parameters, and point clouds.

Category. We leverage WordNet [66] taxonomy that is used by ImageNet [24] to describe multi-hierarchy categories of objects and define 238 common classes. Unlike ImageNet which contains various plants and animals (nature-centric), the objects in our MVImgNet are *found* or *used* in human daily life (human-centric), where 65 classes overlap with ImageNet. The detailed category taxonomy, per-category data distributions, and more sample visualizations of MVImgNet are illustrated in the supplementary material.

4. 3D Reconstruction

4.1. Radiance Field Reconstruction

Pre-review. Recently, a series of generalizable Neural Radiance Fields (NeRF) variants [13, 87, 93, 111] have been proposed to reconstruct radiance field on-the-fly from one/few-shot source views for novel view synthesis.

| Method | Diffuse Synthetic 360° [80] | | | Realistic Synthetic 360° [64] | | | Real-world 360° Objects [74] | | |
|---------------------|-----------------------------|--------------|--------------|-------------------------------|--------------|--------------|------------------------------|--------------|--------------|
| | PSNR↑ | SSIM↑ | LPIPS↓ | PSNR↑ | SSIM↑ | LPIPS↓ | PSNR↑ | SSIM↑ | LPIPS↓ |
| Train from scratch | 37.17 | 0.990 | 0.017 | 25.49 | 0.916 | 0.100 | 22.18 | 0.714 | 0.365 |
| MVImgNet-pretrained | 37.66 | 0.990 | 0.014 | 27.26 | 0.930 | 0.071 | 24.67 | 0.740 | 0.310 |

Table 3. NeRF quantitative results on three different levels of test sets.

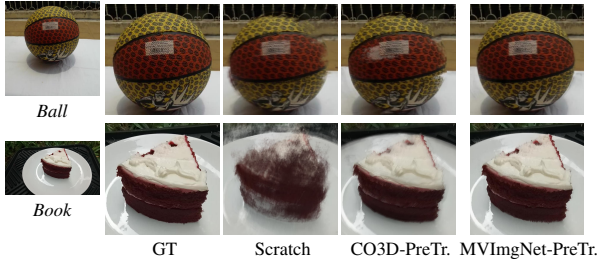


Figure 4. NeRF qualitative comparison of **train-from-scratch** IBRNet, CO3D [74]-pretrained IBRNet and **MVImgNet-pretrained** IBRNet [93].

What can MVImgNet do? Training NeRFs that can generalize to unseen objects requires learning 3D priors from a huge amount of multi-view images. Existing state-of-the-arts either resort to learning on large-scale synthetic data [13, 87, 111], or adopt a mixed use of synthetic data and a small self-collected real dataset [93]. However, the synthetic data introduces a big domain gap with real-world objects, only a few real scenes cannot remedy this defect. We argue that: *our MVImgNet perfectly fits the huge data demand of learning-based generalizable NeRF methods.*

To verify this, we choose IBRNet [93] as the baseline and conduct an empirical study. We pretrain IBRNet on the full MVImgNet dataset then finetune on the training datasets used in IBRNet [93] for a few iterations, and compare with the original train-from-scratch IBRNet model in terms of generalization capability (*i.e.*, generalizing to unseen scenes with only few-shot inputs). For fairness, we evaluate all methods under the same protocol of IBRNet.

Here comes a challenge about *how to evaluate* the generalization ability of NeRFs, since there is no official benchmark for this. To this end, we employ three different *third-party* object-centric datasets to form the test set. 1) The diffuse synthetic 360° object dataset [80] which contains 4 Lambertian objects. 2) The realistic synthetic 360° object dataset [64] which consists of 8 realistically fabricated objects. 3) The real-world 360° object dataset [74] which includes 88 real-world scenes from different lighting conditions. To summarize, the whole test set comprises 100 objects from 56 distinct categories, ranging from the synthetic domain to the real-world domain, which is considered to be an impartial evaluation set for generalization ability.

The quantitative and qualitative results are respectively shown in Tab. 3 and Fig. 4. Evidently, pretraining on MVImgNet improves the generalization ability of the model by a large margin. Moreover, we perform the same pretraining on CO3D [74] and MVImgNet-*small* (a random subset

| Where to pretrain | Real-world 360° Objects [74] | | |
|------------------------|------------------------------|--------------|--------------|
| | PSNR↑ | SSIM↑ | LPIPS↓ |
| CO3D [74] | 24.01 | 0.732 | 0.339 |
| MVImgNet- <i>small</i> | 24.08 | 0.736 | 0.316 |
| MVImgNet | 24.67 | 0.740 | 0.310 |

Table 4. NeRF quantitative comparison with CO3D [74].

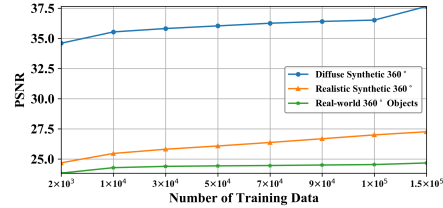


Figure 5. PSNR of IBRNet pretrained by a **different number of MVImgNet data** (higher is better).

of MVImgNet, which owns the same scale as CO3D). As shown in Tab. 4 and Fig. 4, MVImgNet shows greater power than CO3D [74]. The implementation details can be found in the supplementary material.

More data, more power. Fig. 5 shows that an apparent rising trend of generalization metrics can be observed with the increase of training data.

4.2. Multi-view Stereo

Pre-review. Multi-view Stereo (MVS) [30] is a classical task in 3D computer vision, with the goal of reconstructing 3D geometry from multi-view images. Conventional methods [31, 46, 77, 114] reconstruct 3D geometry by finding the patches matched with different images and estimating the depth according to the extrinsic camera. In recent years, deep learning methods are introduced into MVS to solve the issues such as weak textures, and non-laplacian spheres. Two popular end-to-end methods MVSNet [109] and R-MVSNet [110] propose to encode the multi-view images and build a cost volume for predicting depth maps. Under the supervision of large-scale RGB-D datasets [2], they outperform conventional patch-matched-based approaches. However, these methods require massive amounts of RGB-D data, which is always difficult to acquire. This drives the emergence of self-supervised MVS methods [12, 25, 102, 107].

What can MVImgNet do? We demonstrate that our MVImgNet is capable of benefiting the *data-efficient* MVS with limited training examples, which is practically meaningful considering MVS always requires the burdensome collection of RGB-D data.

We pretrain a self-supervised MVS method, JDACS [102], on MVImgNet. Our implementation follows the original settings of JDACS. Then, we select DTU [2] dataset with 79 training samples and 22 test samples. We perform the *data-efficient* evaluation with limited training data, where the MVImgNet-pretrained MVSNet is finetuned on 5%, 15%, and 25% of DTU training samples, and eval-

| Ratio | 2mm \uparrow | 4mm \uparrow | 8mm \uparrow |
|-------|----------------------|----------------------|----------------------|
| 5% | 48.61 / 50.10 | 65.18 / 67.97 | 75.69 / 78.58 |
| 15% | 54.74 / 54.68 | 70.96 / 72.04 | 80.32 / 81.73 |
| 25% | 57.29 / 58.63 | 74.41 / 75.20 | 83.68 / 84.28 |

Table 5. **MVS depth map accuracy** on DTU evaluation set under **different ratios** of DTU training samples, in terms of **training from scratch / MVImgNet-pretrained** (higher is better).

| Where to pretrain | 2mm \uparrow | 4mm \uparrow | 8mm \uparrow |
|------------------------|----------------|----------------|----------------|
| CO3D | 46.18 | 66.72 | 78.39 |
| MVImgNet- <i>small</i> | 47.73 | 66.53 | 78.15 |
| MVImgNet | 50.10 | 67.97 | 78.58 |

Table 6. **MVS depth map accuracy** comparison with CO3D [74] on DTU evaluation set. Pretrain on MVImgNet, MVImgNet-*small* or CO3D, and finetune using 5% of DTU training samples.

uated on the DTU test set. Tab. 5 reports the accuracy given different thresholds of the error between the predicted and ground truth depth map, which indicates that the MVImgNet-pretrained model is capable of improving the model trained from scratch by a large margin under the data-efficient setup. Furthermore, we perform pretraining using CO3D [74] and MVImgNet-*small*. Tab. 6 indicates that our MVImgNet is stronger than CO3D, and MVImgNet-*small* shows comparable power as CO3D. For more implementation details, please see the supplementary material.

We advocate benchmarking NeRF and MVS methods with the help of pretraining on MVImgNet.

5. View-consistent Image Understanding

5.1. View-consistent Image Classification

Pre-review. As indicated by Dong *et al.* [26], although humans can easily recognize one object from different views, deep learning models can hardly do that robustly. MVImgNet provides numerous images from different viewpoints, so we hope to enhance the model’s view consistency with the help of MVImgNet, which is significantly important for realizing human-like intelligence.

What can MVImgNet do? One naive approach is to finetune the ImageNet-pretrained ResNet-50 [44] on our MVImgNet. However, such an approach will be problematic due to the categories of two datasets are very distinct, which may cause catastrophic forgetting issues [50].

For this reason, we create a *new training set*, namely **MVI-Mix**, by mixing the original ImageNet data with MVImgNet. Specifically, we randomly sample 5 *consecutive* frames of each video in MVImgNet, and mix the multi-view images with original ImageNet data. We also build another two artificial training sets, namely MVI-Gap and MVI-Aug, that only differ MVI-Mix with image views. **MVI-Gap** samples the 5 *non-consecutive* frames that have much larger view differences. **MVI-Aug** samples 1 frame from each video of MVI-Mix and applies 4 *different data augmentations* (*i.e.*, random color jittering, grid mask, ro-

| Dataset | Confidence Var | Accuracy |
|---------------|----------------|---------------|
| ImageNet-only | 0.207 | 53.09% |
| MVI-Aug | 0.105 | 71.48% |
| MVI-Gap | 0.103 | 77.23% |
| MVI-Mix | 0.102 | 77.31% |

Table 7. **View-consistent image classification results** on MVImgNet test set using **fully-supervised ResNet-50** [44]. **Adding MVImgNet for training improves the view consistency** (smaller Var and higher Acc indicate better view consistency).

| | Train: CO3DI-Mix | Train: MVI-Mix |
|----------------|--|---|
| Test: CO3D | Var: 0.104 Acc: 91.25% | Var: 0.155 (+0.051) Acc: 84.83% (-6.42%) |
| Test: MVImgNet | Var: 0.188 (+0.086) Acc: 57.93% (-19.38%) | Var: 0.102 Test: 77.31% |

Table 8. **View-consistent image classification** comparison with CO3D [74]. The *performance drops* when train on CO3DI-Mix and test on MVImgNet (**blue number**) are much larger than the opposite (**red number**), which means that MVI-Mix pretrained model is more robust to multiview consistency than CO3DI-Mix pretrained model.

tation and erase, respectively) to it, which aims to differentiate the multi-view augmentation from the normal data augmentations. We compare the *variance* of the softmax confidence and the accuracy on MVImgNet *test set* for examining the view consistency. As illustrated in Tab. 7, adding our MVImgNet data for training can effectively improve the model’s view consistency and accuracy. The test dataset used for all experiments is MVImgNet test dataset. In addition to using the convolution-based network (*i.e.*, ResNet-50), we also apply the *Transformer*-based architecture, DeiT-Tiny [85]. The results are 48.76% accuracy and 0.225 Var on ImageNet-only, VS 0.122 Var (**0.103** \downarrow) and 73.88% (**25.12** \uparrow) accuracy on MVI-Mix. This leads to a unanimous conclusion.

We further construct CO3DI-Mix (corresponding to MVI-Mix) as the mixer of CO3D [74] & ImageNet under the same ratio of MVImgNet & ImageNet in MVI-Mix. As illustrated in Tab. 8, MVImgNet brings more benefits than CO3D for view-consistent image recognition.

5.2. View-consistent Contrastive Learning

Pre-review. Contrastive Learning (CL) is one mainstream of self-supervised training techniques [16–19, 35, 40, 84]. One key factor of CL is the construction of positive/negative pairs, *e.g.*, MoCo-v2 [17] treats an image with different augmentations, *a.k.a.* **views**, as the positive pair.

What can MVImgNet do? One natural question is: *can the viewpoints of MVImgNet serve as the positive pairs for CL?* To answer this question, we finetune the off-the-shelf ImageNet-pretrained MoCo-v2 on MVImgNet. For each iteration, we randomly sample two frames from the same video as the positive pair and apply the original data augmentations used in MoCo-v2 [17]. Meanwhile, the frames from other videos will be treated as their negatives.

| Training scheme | Confidence Var | Accuracy |
|-----------------|----------------|---------------|
| w/o finetune | 0.098 | 70.26% |
| w/ finetune | 0.086 | 71.22% |

Table 9. **View-consistency classification results** under the **self-supervised contrastive learning** regime on MVImgNet test set. **Finetuning MoCo-v2 [17] on MVImgNet improves the view consistency.**

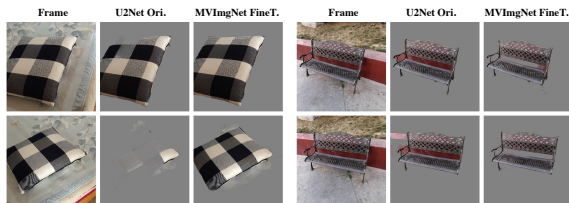


Figure 6. Qualitative comparison between **MVImgNet-finetuned U2Net [73]** and **original U2Net** for salient object detection (SOD). Left: **finetuning on MVImgNet** improves the performance on a *hard* view. Right: **finetuning on MVImgNet** improves the performance on two consecutive hard views.

The MVImgNet-finetuned model is finally evaluated on the MVImgNet test dataset for examining the view consistency, where we compare the variance and mean of the softmax confidence and the accuracy. As Tab. 9 shows, finetuning on MVImgNet with CL can also improve both the model’s view consistency and accuracy. More implementation details of view-consistent image classification is described in the supplementary material.

In the future, it is highly recommended to regard view-consistency as a criterion for evaluating the image recognition task, and utilize MVImgNet to pretrain the models.

5.3. View-consistent SOD

Pre-review. Salient Object Detection (SOD) aims to segment the most visually prominent objects in an image. Although remarkable progress has been made recently, it remains lots of challenges.

What can MVImgNet do? We test a state-of-the-art SOD model U2Net [73] on our MVImgNet. As Fig. 6 shows, U2Net failed to segment “hard” views, even though some views can be segmented with few flaws. Despite such a disappointment, the inconsistent predictions of different views caught our attention: *can we improve the SOD models with multi-view consistency?*

We propose to leverage the multi-view consistency to improve SOD with the help of optical flows. Specifically, given two consecutive frames, we first calculate their optical flow and warp the flow to the segmentation mask of one of the frames. Then, a consistency loss can be calculated between the warped mask and the mask of another frame. For ease of implementation, we directly finetune U2Net on our MVImgNet. To prevent the catastrophic forgetting issue [50], in addition to the MVImgNet, we also use the original training data DUTS-TR [92]. For the “hard” views



Figure 7. Some 3D point clouds sampled from MVPNet.

(IoU ≤ 0.7) on our MVImgNet test set, the model finetuned on our MVImgNet can bring a 4.1% IoU improvement (see Fig. 6 for qualitative comparison). The implementation details of view-consistent SOD can be found in the supplementary material.

6. MVPNet for 3D Understanding

6.1. MVPNet Dataset

Derived from the dense reconstruction on MVImgNet (as mentioned in Sec. 3.2), a new large-scale real-world 3D object point cloud dataset – MVPNet, is born, which contains 87,200 point clouds with 150 categories. Fig. 7 shows some examples of MVPNet. As listed in Tab. 2, compared with existing 3D object datasets, our MVPNet contains a conspicuously richer amount of real-world object point clouds, with abundant categories covering many common objects in the real life. The detailed category taxonomy per-category data distributions of MVPNet are illustrated in the supplementary material.

6.2. 3D Point Cloud Classification

In this work, we focus on point cloud classification. We believe that future works may also utilize our dataset to help much more 3D understanding tasks such as indoor-scene parsing, outdoor-environment perception, pose estimation, and robotics manipulation.

Pre-review. We advocate paying more attention to *real-world* setup, which is more feasible for real applications. ScanObjectNN [89] has been manifested as the most challenging point cloud classification benchmark so far, so we choose it for the major comparison with our MVPNet.

What can MVPNet do? We show that pretraining on MVPNet is able to aid the performance of real-world point cloud classification [36, 39, 62, 71, 72, 94, 97, 105, 106]. We pretrain several models on MVPNet, and finetune them on ScanObjectNN.

Two settings are considered for evaluation. First is PB_T50_RS in ScanObjectNN with small perturbation, translation and rotation on point cloud. Another is adding heavy rotation on PB_T50_RS, to create a more challenging setting. The results are shown in Tab. 10, where pretraining on MVPNet is able to increase the classification accuracy under most circumstances.

| Method | Add Random Rotation | | PB.T50_RS | |
|-----------------|---------------------|----------------------|----------------------|----------------------|
| | from scratch | pretrained | from scratch | pretrained |
| PointNet [71] | 60.57 / 55.20 | 64.25 / 59.29 | 70.63 / 67.28 | 67.73 / 64.12 |
| PointNet++ [72] | 76.50 / 73.42 | 78.76 / 76.54 | 78.80 / 75.70 | 80.22 / 76.91 |
| DGCNN [94] | 80.50 / 78.45 | 80.42 / 78.20 | 79.44 / 76.24 | 82.36 / 80.08 |
| PointMLP [62] | 83.69 / 82.54 | 84.87 / 83.71 | 85.64 / 84.14 | 85.98 / 84.38 |
| CurveNet [97] | 73.96 / 69.96 | 78.99 / 76.59 | 74.27 / 69.43 | 83.68 / 81.17 |
| GDA Net [106] | 80.33 / 79.14 | 83.59 / 82.29 | 79.01 / 75.91 | 83.90 / 82.51 |
| PACConv [105] | 70.91 / 65.70 | 76.21 / 72.47 | 72.88 / 68.60 | 76.91 / 73.45 |
| PCT [36] | 81.32 / 79.17 | 82.08 / 80.41 | 77.46 / 73.64 | 84.20 / 81.94 |
| PointMAE [67] | 83.17 / 80.75 | 86.19 / 84.60 | 77.34 / 73.52 | 84.13 / 81.92 |

Table 10. **ScanObjectNN real-world point cloud classification results.** The comparison is between the **train-from-scratch** model and **MVPNet pretrained** model. The metric is **overall / average accuracy**.

| Method | PB.T50_RS | | |
|------------|----------------------|------------------------|----------------------|
| | PreTr. on MVPNet | PreTr. on MVPNet-small | PreTr. on CO3D |
| PointNet++ | 78.90 / 77.11 | 79.00 / 76.78 | 78.79 / 77.20 |
| CurveNet | 83.68 / 81.17 | 73.92 / 68.92 | 73.78 / 69.62 |
| PointMAE | 84.13 / 81.92 | 81.85 / 79.25 | 81.40 / 78.87 |

Table 11. **ScanObjectNN real-world point cloud classification comparison with CO3D [74].** Pretrain on MViMgNet, MViMgNet-small or CO3D, and finetune on ScanObjectNN. The metric is **overall / average accuracy**.

6.3. Self-supervised Point Cloud Pretraining

Pre-review. Self-supervised learning has been exploited for 3D object point cloud understanding [59, 67, 91, 113].

What can MVPNet do? In Tab. 10, PointMAE [67] pretrained on our MVPNet outperforms the state-of-the-art methods when finetuned on ScanObjectNN, proving the benefit of MVPNet on the self-supervised learning regime for real-world point cloud classification. Tab. 11 also shows that pretraining on MVPNet is more powerful than CO3D [74] for real-world point cloud classification.

6.4. MVPNet Benchmark Challenge

We present the MVPNet benchmark challenge for real-world point cloud classification, which contains 69,760 training and 17,440 testing samples. The results of various methods are shown in Tab. 12.

MVPNet is more challenging than ScanObjectNN. We firstly train models on ScanObjectNN, then conduct the test on MVPNet, which is concluded in Tab. 13. On the opposite, we also train on MVPNet and test on ScanObjectNN, which is listed in Tab. 14. Comparing Tab. 13 and Tab. 14, the *accuracy drops* are significantly *larger* when training on ScanObjectNN and testing on MVPNet, which verifies the greater challenge of our MVPNet. All the experiments in 3D understanding strictly follow the original settings of the selected backbone networks.

MVPNet is suggested for investigating 3D point cloud understanding in the future.

7. Conclusion

We have introduced MViMgNet, a large-scale dataset of multi-view images, which is efficiently collected by shoot-

| Method | Overall / Average Accuracy |
|-----------------|----------------------------|
| PointNet [71] | 70.72 / 54.46 |
| PointNet++ [72] | 79.15 / 58.24 |
| DGCNN [94] | 86.49 / 63.98 |
| PointMLP [62] | 88.89 / 73.64 |
| CurveNet [97] | 88.88 / 75.37 |
| GDA Net [106] | 89.54 / 68.41 |
| PACConv [105] | 83.35 / 59.13 |
| PCT [36] | 91.49 / 75.41 |

Table 12. Quantitative results on our **new MVPNet benchmark for real-world point cloud classification**.

| Method | train: MVPNet | train: ScanObjectNN |
|-----------------|---------------|---------------------------------|
| | test: MVPNet | test: MVPNet |
| PointNet++ [72] | 79.15 / 58.24 | 15.13 (-64.02) / 7.96 (-50.28) |
| CurveNet [97] | 88.88 / 75.37 | 46.95 (-41.93) / 28.24 (-47.13) |

Table 13. Quantitative comparison while **training on ScanObjectNN, testing on MVPNet**. The evaluation metric is **overall / average accuracy**.

| Method | train: ScanObjectNN | train: MVPNet |
|-----------------|---------------------|---------------------------------|
| | test: ScanObjectNN | test: ScanObjectNN |
| PointNet++ [72] | 76.50 / 73.42 | 40.35 (-36.15) / 33.59 (-39.83) |
| CurveNet [97] | 73.96 / 69.96 | 51.84 (-22.12) / 46.27 (-23.69) |

Table 14. Quantitative comparison while **training on MVPNet, testing on ScanObjectNN**. The evaluation metric is **overall / average accuracy**.

ing videos of real-world objects. The multi-view nature endows our dataset with 3D-aware visual signals, making MViMgNet a soft bridge to link 2D and 3D vision. To probe the power of MViMgNet, we conduct a host of pilot experiments on various visual tasks, including radiance field reconstruction, multi-view stereo, and view-consistent image understanding, where MViMgNet demonstrates promising effectiveness, expecting more future explorations. As a bonus of MViMgNet, a point cloud dataset – MVPNet is derived. Experiments show MVPNet can benefit real-world 3D object classification. As a broader impact on society, our datasets *delineates* a world – that is closer to a colorful and vivid real 3D world – where we human lives.

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