PennSyn2Real: Training Object Recognition Models without Human Labeling

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Abstract—Scalability is a critical problem in generating training images for deep learning models. We propose PennSyn2Real - a photo-realistic synthetic dataset with more than 100,000 4K images of more than 20 types of micro aerial vehicles (MAV) that can be used to generate an arbitrary number of training images for MAV detection and classification. Our data generation framework bootstraps chroma-keying, a matured cinematography technique with a motion tracking system, providing artifact-free and curated annotated images where object orientations and lighting are controlled. This framework is easy to set up and can be applied to a broad range of objects, reducing the gap between synthetic and real-world data. We demonstrate that CNNs trained on the synthetic data have on par performance with those trained on real-world data in both semantic segmentation and object detection setups.

I. INTRODUCTION

Safety-critical operation in applications such as autonomous driving and surveillance require highly accurate predictions from deep learning methods. To achieve this high accuracy, methods often require a surprisingly large amount of training data. In the context of supervised learning, the prevailing approach in deep learning, generating training data requires both collecting and labeling data. Collecting big training data that capture all potential conditions under which the AI system would operate is an unsolved problem. Annotating such a massive quantity of data is another hurdle. These challenges drive the development of alternative methods that are potentially more scalable and controllable.

There is a huge interest in leveraging synthetic data due to its promise of dramatically simplifying the training process. On top of the seemingly infinite amounts of data that can be generated, synthesized data has perfectly accurate labels that human-labeling can never achieve. Indeed, authors in [1], [2] have demonstrated that synthetic datasets are a cost-effective alternative and supplement to manually labeled data, with good transferability.

The primary challenge of these fabricated datasets is to reproduce visually realistic images with minimal artifacts. The synthetic data generated using game engines such as Unity are not yet ideal for training state-of-the-art (SoTA) DNNs due to a limited syn-to-real transferability. The key reason for this issue, as Geirhos et al. [3] show empirically, is that SoTA DNNs often fail to utilize the shape of an object and instead heavily rely on visual textures. Despite recent successes in synthetic-to-real domain adaptation and refinement, there is still a room for advanced syn-to-real transferability.

An alternative way to generate synthetic data with realistic textures is to superimpose real object images onto real background images. This approach has a couple of advantages over the aforementioned approaches in twofolds. Firstly, as both object images and background images are real, this approach can generate more realistic training images. Secondly, by decoupling the data generation process into object image extraction and background image acquisition, ones can have a more feasible way to control the distribution of the training images so as to guarantee that there is minimal data shift between the training and the test sets.

While the object images can be extracted from human-labeled-images, this method can introduce a boundary artifacts due to the inaccuracy of human labeling. To mitigate these artifacts, we instead utilize the chroma-keying technique which has been widely used in cinematography to achieve the highest quality of extracted object images. Fig. ?? shows examples of MAV images extracted from this process. Fig. 1 visualizes the real-world images in comparison with the synthetic images generated by superimposing extracted object images onto the background images captured in the same environment.

To gain control over the distribution of object’s orientations in the training dataset, we use a motion capture system, as shown in Fig. ?? to track the camera and object
during video capturing. This step provides object orientations associated with every single object image generated. While our work focuses on object detection and tracking problems, this orientation information can be useful for other vision problems such as pose estimation.

The popularity and accessibility of MAVs for both commercial or recreational use have surged. While being highly useful in various applications, MAVs can also pose security issues to sensitive areas such as airports and military bases. It is, therefore, crucial to develop a fine-grained classification method that is capable of detecting different types of MAVs. This task is challenging due to a large number of types of MAVs, and cluttered environments in which MAVs often operate. We introduce PennSyn2Real, a synthetic dataset consisting of more than 100,000 4K images of more than 20 types of MAVs including our custom MAVs and commercial MAVs such as DJI Mavic Pro, Skydio 2, and Autel 1. Furthermore, we demonstrate the transferability of our dataset by using these synthetic data to train CNNs to detect MAVs in various indoor, outdoor, and cluttered environments. In short, this work centers around the following contributions,

1) A large scale MAV dataset for multi-MAV detection and recognition.
2) A data generation framework for scalable image data generation for training CNNs.
3) Demonstration the use of the synthetic data to train object detection, semantic segmentation CNNs.

II. RELATED WORKS

A. Synthetic Datasets

Alexey et al. [4], Butler et al. [5], and Kaneva et al. [6] are early works on using photo-realistic imagery for evaluation and training. In these works, authors consider photo-realistic imagery as a feasible way to obtain large datasets with ground truth which would be otherwise hard to do. However, the artifacts appearing in the images limit the performance of these datasets.

Recent advances in photorealistic computer graphics platforms have made synthetic data a popular choice for training DNNs. For example, the SYNTHIA dataset [7], [8], a synthetic dataset generated using game engines, is shown to improve CNN’s performance on a scene segmentation task. The virtual KITTI dataset [1], [9], another game engine-based synthetic dataset, has a broader scope. Their system can generate training data for a wider range of applications, including semantic segmentation and depth estimation. Both datasets, however, focus on driving scenarios and because they are generated using game engines, there is still a gap between synthetic data and real-world data.

Unlike these datasets, PennSyn2Real is unique in that it combines the realistic appearance of an actual object and real background to generate arbitrary amounts of high-quality training images with a minimal number of artifacts. Moreover, we use the motion capture system to control the variance in the object’s orientations. PennSyn2Real’s methodology can be useful for different applications from object recognition to pose estimation.

Wei et al. [10] and Follman et al. [11] are some datasets generated using a method close to our framework. However, they focus on warehouses with indoor settings. All evaluations are with the dataset collected with the same settings.

B. MAV datasets

The literature has seen increasing interests in vision-based MAV detection and tracking. Unlu [12] and Wyder [13] develop deep learning-based approaches to detect MAVs using one or multiple cameras. Wyder et al. [13] also provide 58,647 labelled MAV images. However, they are mostly indoor and specific to one single target MAV. Jing et al. [14] introduce 70,000 images with only a single type of MAV. In addition to their limitations of a variety of MAVs, these datasets are tailored specifically to specific background environments. In contrast, PennSyn2Real features more than 100,000 4K images of more than 20 types of different MAVs which can be used to generate an endless number of training images using different background images.

III. DATA COLLECTION PROCESS

We collect 4K HDR videos of an object against a green background as shown in Fig. 2. The background and object are separately lit by lightboxes to ensure uniform lighting and better chroma-keying. The object is on a powered rotating turntable, and the camera is on a stabilizing gimbal. In this way, by the gimbal adjusting the altitude and the turntable the azimuth, we control 2 degrees of freedom of rotation. The final degree of freedom about the camera axis can be controlled by rotating the image in the superimposing step, and the translational degrees of freedom by translation and scaling of the object image. We show the distribution over this space of viewing angles in Fig. 4 and note that we well-cover the top-half of this distribution in this dataset, with exceptions being the bottom and very top of the object. We additionally attach markers to the camera and turntable and track both in a motion capture system to additionally generate pose labels. Motion capture and camera synchronization is done in post-processing by aligning a rapid rotation of the camera made at the beginning of each video.

Once videos are collected, they are processed by our synthetic image generation pipeline, shown in Fig. 3. We use DaVinci Resolve, a commercial video editing software, to remove color bleed from the green screen and generate the chroma-keyed segmentation. These two channels are exported to video and loaded by our image synthesizer. At this point, we use the keyed mask as an alpha channel for compositing with a background image. A number of parameters can be adjusted or randomized for data augmentation, including image scaling, position, and rotation to cover the remaining portion of the possible viewing poses for the object. We also adjust image blur and brightness for the object and background separately.
IV. EXPERIMENTS

In this section, we present experimental results on using the synthetic data to train CNNs for MAV detection and segmentation problems.

A. Semantic Segmentation

In this section we use the ground-truth semantic segmentation annotations given from Nguyen et al. [15] to evaluate different state-of-the-art semantic segmentation methods.

B. Object Detection

We use 7 Youtube video queried from searching keywords such as green lawn, back yard to obtain background images. We then split 5 videos for training and 2 videos for validation purposes. We use images from 3 types of MAVs to generate about 30,000 training samples and 10,000 validation samples.

The test set features these MAVs flying in an outdoor environment. Fig. shows the qualitative results on the real-world test set. Fig. shows an example of the detection results.


data-driven training samples.

| Manual-Labeled Data | Synthetic Data |
|---------------------|----------------|
| IoU                 |                |
|                       | U/Net | EfNet | E/Net |
| FN Rate              |       |       |
| FP Rate              |       |       |

TABLE I: Top-3 Performance models on [15] dataset

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