A Dense Depth and Forground images dataset of Stray Animals (some name XYZ)

January 11, 2021

Abstract

Dataset creation
limitation lacking ground truth
Depth and foreground prediction

1 Introduction

we introduce XYZ, a dataset that contains millions of depth and forground images of stray animals derived from few hundreds of images. XYZ is the first dataset which has stray animals. The dataset is available for download at ....link... This is an RGBDM dataset that pair images with depth and mask. The datasets which involve depth cannot be created using crowd source annotation, instead they rely on 3D range sensors. This XYZ is experimentally created with the help of existing depth predictors and foreground creators.

XYZ can also be used for automonous driving

Depth information is integral to many problems in robotics, including mapping, localization and obstacle avoidance for terrestrial and aerial vehicles, and in com- puter vision, including augmented and virtual reality[5]. The reason for using existing depth predictors for the creation of new dataset - depth sensors and monocular cameras are expensive. we used existing accurate depth predictor [reference]

if we can come up with limitations of existing rgbd datasets... then we can write This paper present the XYZ dataset in an effort to address the aforementioned limitations of exisitng RGBD datasets.

Figure 3 represents a few representative examples from XYZ

The most important feature of XYZ is

2 Related Work

[*** sentences need to be reframed with the help of Abhinav sir A variety of RGBD datasets in which images are paired with corresponding depth maps(D)

Figure (1) Sample Record which contains the background image, a cow overlayed on top of background, its mask and depth images

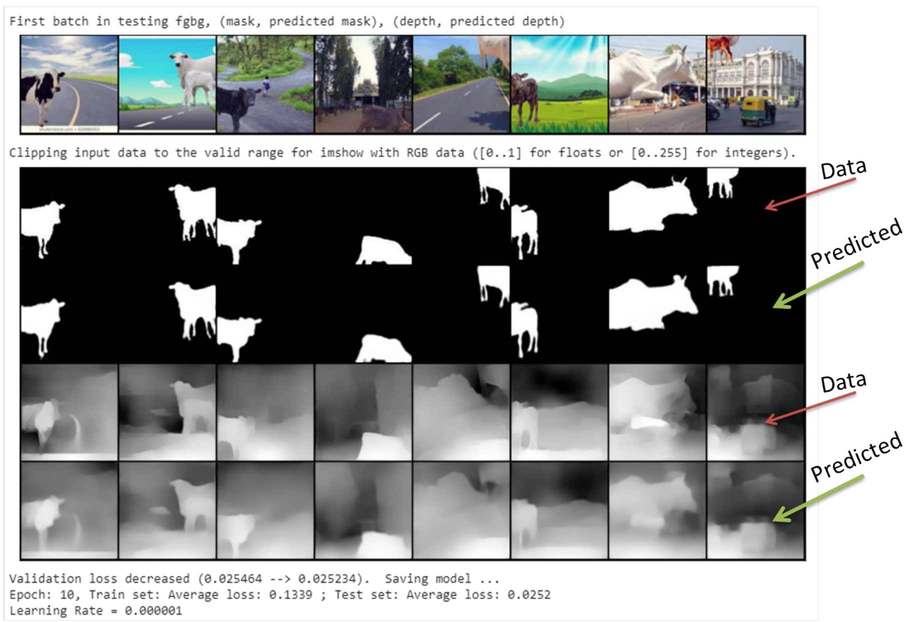


Figure (2) Sample Record which contains the background image, a cow overlayed on top of background, its mask and depth images

have been proposed through the years. Available RGBD datasets kitti dataset [1], the Synthia dataset [2], Make3D dataset [3], NYU dataset [4]

It is the best known RGBD dataset collected using a vehicle equipped with a sparse Velodyne VLP-64 LiDAR scanner and RGB cameras, and features street scenes in and around the German city of Karlsruhe. Primary application of this dataset involves perception tasks in the context of self-driving.

Synthia is a street scene dataset with depth maps of synthetic data, requiring domain adaptiation to apply to real world settings.

Cityscapes [reference] provides a dataset of street scenes, albeit with more diversity than KITTI.

Sintel [reference] is another synthetic dataset which includes outdorrs sences.

Megadepth [reference] is a large-scale dataset of outdoor internet images,

Figure (3) Sample Record which contains the background image, a cow overlayed on top of background, its mask and depth images

with depth maps recon- structed using structure-from-motion techniques, but also lacking in ground truth depth and scale.

Make3D [reference] provides RGB and depth information for outdoor scenes

The NYUv2 dataset [reference] is widely used for monocular depth estimation in indoor environments. The data was col- lected with a Kinect RGBD camera, which provides sparse and noisy depth returns. These returns are generally in- painted and smoothed before they are used for monocular depth estimation tasks. As a result, while the dataset in- cludes sufficient samples to train modern machine learn- ing pipelines, the “ground-truth” depth does not necessarily correspond to true scene depth. ***]

3 The XYZ dataset

we designed the dataset with the following objectives... 1. dataset which dedicately include stray animals, as animals move without any restrictions in the small cities of India. 2. self driving cars should be able to identify animals 2. dataset should provide accurate dense depth maps. 4. dataset should provide foreground images

3.1 Data Acquisition

3.2 Data Curation and Processing

3.3 Data Statistics

4 Experiments

In this section, we provide a baseline for monocular depth estimation on the XYZ dataset

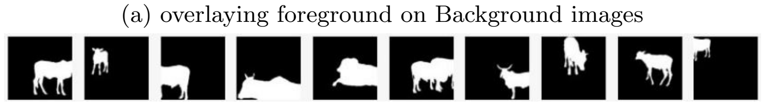
(a) Background images

(b) Foreground images

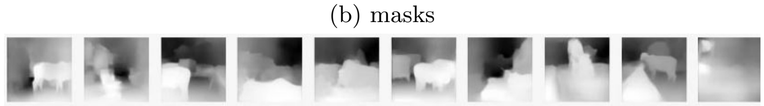
(c) Foreground mask

Figure (4) Fig a. shows 10 sample images from the 100 background images used for dataset generation. Fig. b shows 10 sample images from the 200 foreground images and Fig c. showcases the corresponding masks of the foreground images.

(a) overlaying foreground on Background images



(b) masks



(c) depths

Figure (5) Fig a. placing foreground over background with random loacation and scale. Fig. b and c show the corresponding masks and depths of Fig. a

Type of Image	Total	Mean	Standard Deviation
fg_bg	400000	(0.50610699, 0.5250236, 0.51219183)	(0.28525343, 0.24801724, 0.24747186)
mask	400000	(0.13532567,)	(0.33999708,)
depth	400000	(0.57016144,)	(0.25914387,)

```
|---custom_data
    |---bgimages              # contains 100 background images
    |---foreground            # contains 100 foreground png imags and images produced by flipping them (200)
    |---masks                 # contains 200 masks for the above foreground images
    |---output
        |---fgbg              # 400000 images produced by overlaying every fg 20 times on bg
        |---masks             # 400000 respective masks of the fgbg images
        |---masks             # 400000 respective depth images of fgbg images
```

Figure (6) Top-level layout of the dataset (Directory Structure)

4.1 Model

We train two models on the subsets of XYZ and as well as the entire dataset. During training, all networks are trained with the batch size of ...for ... epochs using SGD[reference]. We start with a learning rate 0.0001 and decrease it by one tenth after 20 epochs (this sentence has to bre replaced by my approach). The DNN is fed with a full-resolution image (XXY) and outputs the predicted depth at the resolution (XXY). we employ .. and .. and... for data augmentation.

4.1.1 Model1

Network Architecture Loss calculation

4.2 Evaluation

We evaluate the performance of the model on the valida-tion set using

4.3 Analysis

3.

5 Conclusion

6 Acknowledgement

This paper and the research behind it would not have been possible without the exceptional support and computing facilities of my Institution, Vishnu Institute of Technology.

References

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