

# MineNav: An Expandable Synthetic Dataset Based On Minecraft For Aircraft Visual Navigation

We present a novel synthetic dataset MinNav based on the sandbox game Minecraft. This dataset uses several plug-in program to generate rendered image sequences with time-aligned depth maps, surface normal maps and camera poses. MinNav is a highly scalable dataset, users not only can easily obtain a large number of big-scale 3d scene files in the community, saving modeling time, but also can build specific scenes in the game. what's more, thanks for its open source feature, users can also develop modules to obtain other ground-truth for different purpose in research. Different from other synthetic datasets, our proposed dataset has a community of a large number of players, which can build 3d scenes and obtain tools at a lower cost, and because there are a large number of light and shadow rendering tools, the generated synthetic dataset can be greatly reduced Distribution deviation from real-world data.

Understanding scenes through video is a significant research in visual perception. It includes many classical computer vision tasks, such as depth recovery, surface normal prediction and visual odometry etc. Undoubtedly, data sets are the top priority of research.

Presently datasets[7, 4] has already been applied in industrial such as autonomous driving [3], interactive collaborative robotics [5], and localization and navigation systems [6], etc . But ground-truth of these always suffer the approximately measurement limited by the sensor, or even unavailable, requiring huge cost. Most synthetic dataset[2, 10] based on open-source film makes up for the above shortcomings partly. It also provide a new opportunity for computer vision research. What's more ,the data bias between synthetic data and real-world data is unavoidable problem and limited amount of data, especially the scene, is Gradually unable to meet demand of resent model.

We propose a simply method to generate high quality synthetic dataset based on open-source game Minecraft includes rendered image, Depth map, surface normal map, and 6-dof camera trajectory. This dataset has a perfect ground-truth generated by plug-in program, and thanks for the large game's community, there is an extremely large number of 3D open-world environment, users can find suitable scenes for shooting and build data sets through it and they can also build scenes in-game. as such, We don't need to worry about manual over fitting caused by too small datasets. what's more, there is also a shader community which We can use to minimize data bias between rendered images and real-images as little as possible. Last but not least, we now provide three tools to generate the data for depth prediction ,surface normal prediction and visual odometry, user can also develop the plug-in module for other vision task like segmentation or optical flow prediction.

## 2 Preparatory tools

It is a sandbox video game created by Swedish game developer Markus Persson and released by Mojang in 2011. The game allows players to build with a variety of different

blocks in a 3D procedurally generated world, and has already been a tools in several research[9, 1, 11]. Its minimum component is block sized  $1 \times 1 \times 1$ , and map loading range is a square with  $1536 \times 1536$ , support player to redevelop plug-in module to achieve specific function.

## Replay Mod

is a Modification for the Minecraft which allows players to record and replay their gaming experience with monocular, stereo, or even 360D videos. Player can generate dynamic 3d scene file centered as main player and set camera trajectories manually with adjustable fov. The 3d scene file support rendered by Blender, and also could be rendered in real-time by third-party shader.

## Optifine

is a Minecraft optimization mod. It allows Minecraft to run faster and look better with full support for HD textures and many configuration options. We have developed two shader3 thought it to generate precise ground-truth in sync with image sequences.

## Sildur

Sildur is an open-source shader written in GLSL, it adds shadows, dynamic lighting, and waving grass, leaves and water to increase the reality, reduce the data bias between rendered data and real-data.

## 3 Generation of Datasets

In this paper, we choose a big game map AudiaCity 2.0 (Fig. 4) as scene to build MinNav.

It contains over 1,500 buildings, covering an area of 16 square kilometers and an altitude of 67 meters. including schools, hospitals, libraries, wharves and factories etc, has a good diversity to meet most demand <https://www.planetminecraft.com/project/audia-project-minecraft-city/>. \dirtree.1 MinNav. .2 Grids Number. .3 Trajectory Number. .4 color. .5 frame-number.png. .5 .... .4 depth. .5 frame-number.png. .5 .... .4 timestamp.txt. .4 camera-state.txt. \dirtree.1 Grids Raw Files. .2 grid-number. .3 SceneNumber.mcpr. .3 timelines.json. .3 .... .2 ....

It obviously that the map can not loaded into limited memory all at once, We sampling every 400 meters in both directions divided the whole map into several Grids sized as a  $800m \times 800m$  and saved them as dynamic 3d scene by ReplayMod (Sec. 2). For each grid, we manually set 1 to 3 camera trajectory(ies) over 20ms, and totally generating 168 grid directory including 8800 samples as MinNav which includes color image, depth map, surface normal image and 6-dof camera trajectory.

## Data Description





## 4 Domain Randomization

Using domain randomization[12] is a popular method for introducing more diversity to a synthetic datasets. Some works generate images with different render passes.[2] generates each frame that simulate different aspects of image formation such as smooth shading, specular reflections, and inter-reflections. Although some [10] rendered their self-made scenes in multiple versions, each with random incremental changes to the camera's translation and rotation keyframes. transformations enrich the datasets , they still are similarity preserving.

In addition to generating different scenes to increase the diversity of dataset such as deserts, snow, jungles, lakes, cities, etc., MC also has a time system and a weather system for achieving this (Fig.9). All of them can change the brightness and visibility of a dynamic scene, expanding diversity of dataset in a better way. Every sample-grid can apply to different weather or time for achieving reduction of a network's generalization error. What's more, using different shader for one grid-sample, or adjusting the fog options or motion blur in Replay Mod can also increase the diversity.

## 5 Experiment

The experiments is designed to investigate how MinNav useful is for generalizing to real-world aerial image dataset like VisDrone[14], and shows the running result in several popular algorithms.

### Evaluating the Deviation of data distribution

In this section, we seek to validating the Deviation of data distribution between MinNav and VisDrone compared with kitti[7].

We originally planned to pre-train in MinNav and KITTI respectively through the same model, and then evaluate it in visdrone, confirm which data set is better for generalization on visdrone. However, Due to the absence of ground-truth in VisDrone, We changed our approach. We train an unsupervised model in visdrone, and then quantify the evaluation on MinNav and kitti respectively, and get the quantitative results(See tab.1). The better evaluation results on MinNav means that the data distribution of this dataset is closer to MinNav.

It can be seen that the same model is directly evaluated on MinNav after being trained by KITTI and VisDrone respectively. The latter result is significantly better than the former. It can be seen that although the MinNav data set is a synthetic dataset, it is more than KITTI in data distribution. In order to be close to VisDrone, so for the data model based on aerial images, MinNav is better than kitti for depth estimation tasks.

### Evaluation Results on Recent Works

In this section we trained a depth estimation and odometry estimation model monodepth2[8] on our dataset and the quantitative result are shown in Tab.2

This paper provided a simply method to generate synthetic dataset with ground-truth of depth , surface normal and camera trajectory. Basic texture and geometry information given by Minecraft is obviously not enough for a dataset to training model, while through the high quality shader provided by community, the color image can narrow the data distribution gap as much as possible. What's more By developing module in Minecraft, user can easily obtain needed ground-truth for other computer vision task such as optical flow, segmentation label with a low cost. Traditional synthetic[2, 10] datasets are generated by open source movie and Rendered by professional 3d render software like Blender. thought with a lower threshold of building dataset, it still need users with a tedious work, especially for the large scale scene building. Thanks for large community, The are Massive maps can be easily found on the website and users never worry about the shortage. We further found that recent depth prediction algorithms that perform well on the KITTI benchmark do significantly worse on the MinCV data set, suggesting room for new methods.

There are several ways users can expand our current dataset, These include rendering the color image at higher spatial and temporal resolutions, with different shader or add motion blur, with additional game map, or setting render options as stereo or cubic.

#### Appendix A Normal Vector Color Mapping

In this section we mainly show the color mapping of surface by changing pitch, yaw and roll angle independently. if pitch =absent= $\alpha$  italic\_, then:

$$S_y = (1, \cos \alpha, \sin \alpha) \text{ italic}_S$$

$$\text{end\_POSTSUBSCRIPT italic}_y \text{ start\_POSTSUPERSCRIPT + end\_POSTSUPERSCRIPT}$$

$$\text{end\_POSTSUBSCRIPT} = ( 1 , \text{roman\_cos italic}_\alpha , \text{roman\_sin italic}_\alpha )$$

$$S_z = (1, 1, \cos \alpha) \text{ italic}_S$$

$$\text{start\_POSTSUBSCRIPT italic}_z \text{ start\_POSTSUPERSCRIPT - end\_POSTSUPERSCRIPT}$$

$$\text{end\_POSTSUBSCRIPT} = ( 1 , 1 , \text{roman\_cos italic}_\alpha )$$

$$S_z = (1, \sin \alpha, 1) \text{ italic}_S$$

$$\text{start\_POSTSUBSCRIPT italic}_z \text{ start\_POSTSUPERSCRIPT + end\_POSTSUPERSCRIPT}$$

$$\text{end\_POSTSUBSCRIPT} = ( 1 , \text{roman\_sin italic}_\alpha , 1 )$$

similarly, if yaw =absent= $\beta$  italic\_ or roll =absent= $\gamma$  italic\_ then:

$$S_z = (\sin \beta, 1, \cos \beta) \text{ italic}_S$$

$$\text{start\_POSTSUBSCRIPT italic}_z \text{ start\_POSTSUPERSCRIPT - end\_POSTSUPERSCRIPT}$$

$$\text{end\_POSTSUBSCRIPT} = ( \text{roman\_sin italic}_\beta , 1 , \text{roman\_cos italic}_\beta )$$

$S_x = (\cos, 1, 1)$   
start\_POSTSUBSCRIPT italic\_x start\_POSTSUPERSCRIPT - end\_POSTSUPERSCRIPT  
end\_POSTSUBSCRIPT = ( roman\_cos italic\_ , 1 , 1 )

$S_x = (1, 1, \sin)$   
start\_POSTSUBSCRIPT italic\_x start\_POSTSUPERSCRIPT + end\_POSTSUPERSCRIPT  
end\_POSTSUBSCRIPT = ( 1 , 1 , roman\_sin italic\_ )

$S_x = (\cos, \sin, 1)$   
start\_POSTSUBSCRIPT italic\_x start\_POSTSUPERSCRIPT - end\_POSTSUPERSCRIPT  
end\_POSTSUBSCRIPT = ( roman\_cos italic\_ , roman\_sin italic\_ , 1 )

$S_y = (1, \cos, 1)$   
start\_POSTSUBSCRIPT italic\_y start\_POSTSUPERSCRIPT + end\_POSTSUPERSCRIPT  
end\_POSTSUBSCRIPT = ( 1 , roman\_cos italic\_ , 1 )

$S_y = (\sin, 1, 1)$   
start\_POSTSUBSCRIPT italic\_y start\_POSTSUPERSCRIPT - end\_POSTSUPERSCRIPT  
end\_POSTSUBSCRIPT = ( roman\_sin italic\_ , 1 , 1 )