DANGER: A Framework of Danger-Aware Novel Dataset Generator Extension for Robustness Test of Machine Learning

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Abstract

Benchmark datasets for autonomous driving, such as KITTI, Argoverse, or Waymo are realistic, but they are designed to be too idealistic. These datasets do not contain errors, difficult driving maneuvers, or other corner cases. We propose a framework for perturbing autonomous vehicle datasets, the *DANGER* framework, which generates edge-case images on top of current autonomous driving datasets. The input to DANGER is a photorealistic datasets from real driving scenarios. We present the DANGER algorithm for vehicle position manipulation and the interface towards the renderer module, and present primitive generation cases applied to the virtual KITTI dataset. Our experiments prove that DANGER can be used as a framework for enlarging the current dataset to cover generative corner cases.

1 Motivation

Autonomous vehicles promise to decrease vehicle fatalities and increase safety in the modern automobile. However, the majority of datasets [3, 15, 13, 1, 7] and derived algorithms [4, 16, 8, 11, 10, 6, 2, 14, 18] are used for benchmarking. This causes a weakness: machine learning (ML) models cannot handle real-world unexpected road events [12]. To make ML models more robust, we describe an iterative procedure for creating out-of-domain examples for autonomous driving based on existing AV standard datasets. In summary, our key contributions are: (a) DANGER[1], a framework of Danger-Aware Novel dataset Generator Extension for Robustness test, with user input of vehicle driving trajectories and postures to complete a sequence of frames of data generation. (b) DANGER also supports the movement and deletion of vehicles in individual frames and can simulate illogical special camera failure modes.

2 Method

2.1 Framework Overview

The DANGER framework generates new samples using an object-aware rendering algorithm and a set of primitives. We include five predefined primitives in our DANGER implementation with additional user-defined primitive functionality. In the results section, we use 3D scene de-rendering networks (3D-SDN) [17], an optimal algorithm that generates photo-level realistic synthetic images, as the renderer module to demonstrate the feasibility of our framework. In practice, and the renderer/de-renderer module such as Panoptic Neural Fields can also be selected in practical implementation [9].

[1]Our code and results for the framework and experiments has been open-sourced under the MIT License and is available at: `https://github.com/jayhsu0627/DANGER`.

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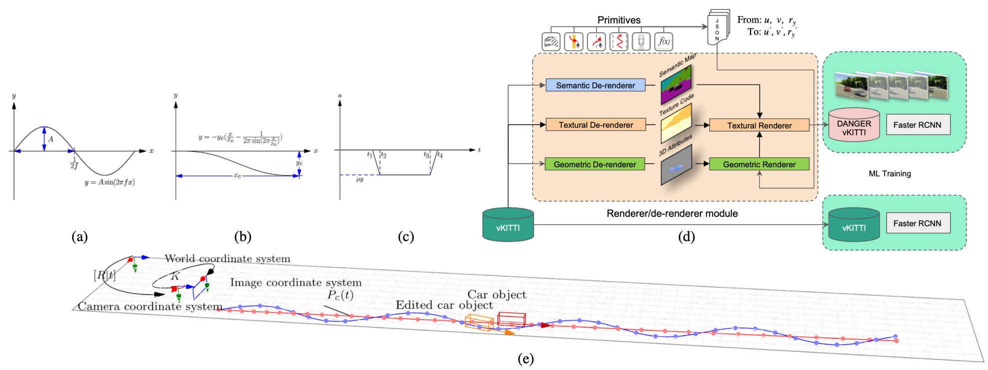

Figure 1: **DANGER architecture**. (a) slalom lane change function (b) cut-in function (c) DANGER contains a renderer/de-renderer module, primitive function module, and generated descriptive file that can help users to develop a wide variety of corner-case images based on any self-driving car datasets that support semantic and 3D annotations (d) the scene `0006` editing is shown in world coordinate.

The 3D-SDN employs an encoder-decoder architecture and has three branches: scene semantics, object geometry and 3D pose, the appearance of objects and the background. As shown in Fig. 1(c), the intentions of each branch are to learn the semantic segmentation of a scene, infer the object shape and 3D pose, and encode the appearance of each object and background segment. Disentangling 3D geometry and pose from the given scene enables 3D-aware scene manipulation with the given target location (u, v), pose r_y, and operations `(delete, modify)` in image coordinate.

Primitives We define a set of vehicle primitives to augment the input dataset. We represent five danger-aware primitives: `Disappear`, `Cut-in Opposite`, `Cut-in`, `Lane Change`, and `Reverse`. The point is that these primitives can be extended by composition and addition to cover larger error cases. For example, perhaps it has been identified that the computer vision algorithm is weak at predicting lane cuttings: when a car changes lanes quickly in front other another car. DANGER can be used to generate many of these cut-in behaviors to be used for training, re-training, and testing.

2.2 Scene Editing Computation

Given any defined function $f(x)$ as target, our approach projects a car object into a new location in the 2D plane under the world coordinate system. Given a image $I \in \mathbb{R}^{W \times H \times 3}$ with known camera intrinsic matrix $\mathbf{K} \in \mathbb{R}^{3 \times 4}$ and camera extrinsic matrix $[\mathbf{R}|\mathbf{t}]$, we can manipulate the position of an object in world, camera, or image coordinate system. $P_c \in \mathbb{R}^{4 \times 1}$ is the 3D point position in camera coordinates and $P_w \in \mathbb{R}^{4 \times 1}$ is the 3D point position in world coordinates. A camera extrinsic matrix $\mathbf{M} \in \mathbb{R}^{4 \times 4}$ is used to denote a projective mapping from world coordinates to pixel coordinates. The elements of object's center position vector P_c can be acquired from the MOT ground truth data of virtual KITTI [5], and the corresponding P_w will be easily obtained by apply the inverse of frame-dependent matrix $\mathbf{M}$. In the x-z plane, arbitrary vehicle poses can be generated according to the primitive function, where $\mathbf{r}'_y$ is a unit tangent vector to the curve at (x'_w, z'_w) representing the target orientation of the car object.

3 Results and conclusion

We conduct scene editing experiments on publicly available dataset virtual KITTI, as a proxy to KITTI, based on the descriptive files generated by the primitive functions. We show results on virtual KITTI here: `https://github.com/jayhsu0627/DANGER`. In this paper, we proposed a dataset expansion framework for generating hazardous driving scenarios. We hope DANGER can broadly accelerate AI research and value in improving ML model performance while also creating well-distributed, trusted datasets for ensuring safety-critical systems.

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