Artifact: Generating Realistic and Diverse Tests for LiDAR-Based Perception Systems

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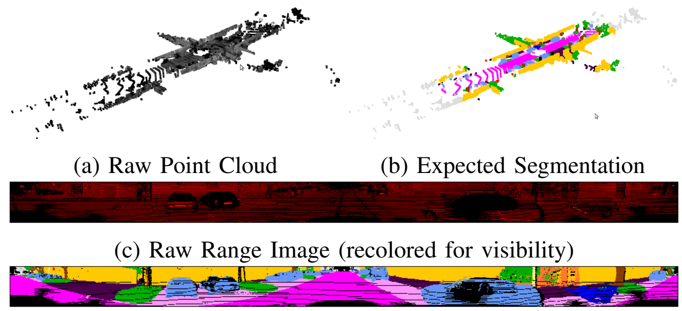
The artifact to evaluate Generating Realistic and Diverse Tests for LiDAR-Based Perception Systems is reusable and publicly released on GitHub along with additional study details and discussion. The Artifact includes the tool, perception systems, evaluation scripts, and data used in the original study and evaluation. The tool is written in Python and containerized in Docker with supporting Unix shell scripts to validate the tool and detailed descriptions for how to set up and extend the evaluation pipeline for adoption in future research. We provide a small data set along with scripts to demonstrate the end-to-end usage of the tool, with detailed instructions on how to obtain and set up the full data set from its authors. In addition to the tool itself, the evaluated versions of each of the perception systems are available along with the data obtained from the study.

I. Introduction

We introduce a new technique for testing LiDAR-based perception systems that takes as input existing real-world labeled LiDAR test cases, as shown in Fig 1, and mutates them to generate novel, realistic test cases that can expand the diversity of tests to explore the long-tail of possible scenes. We provide a research prototype tool that we use to explore and validate the technique. The tool is publicly released at https://archive.softwareheritage.org/browse/origin/directory/?origin_url=https://github.com/less-lab-uva/semLidarFuzz

The data set consists of pairs of LiDAR point clouds (PCs) collected from the real world and a labeling of these PCs based on the semantic interpretation of the points. From this data, the tool will produce realistic and novel test cases consisting of a novel PC and its labeling. Although many data sets may be applicable, our tool uses the publicly available SemanticKITTI [1] data set as the source for the labeled LiDAR data. The tool is written in Python and includes a MongoDB database for storage and supporting shell scripts for initialization. The tool is containerized in Docker with Docker Compose support for ease of use and replication.

Our technique also offers a new paradigm for evaluating the performance of LiDAR perception systems under test (SUTs). The five SUTs evaluated in the study are also containerized in Docker and publicly available. The tool provides Python code to evaluate the performance of each SUT on the generated test cases, and is extensible to allow for the addition of new SUTs.



(a) Raw Point Cloud (b) Expected Segmentation

(c) Raw Range Image (recolored for visibility)

(d) Expected Segmentation Range Image

Fig. 1: Example LiDAR Point Cloud (PC) used in perception (best viewed on a screen). Fig. 1a shows an example PC in perspective. Figs. 1a and 1c are colored with the reflected intensities of the LiDAR beams. Figs. 1b and 1d are colored with the human-annotated semantic class of each point. Figs. 1c and 1d show a "range image" where the 360° view is projected onto a cylinder and unrolled.

II. Motivation

Autonomous Systems (ASs) operate in safety-critical situations and preserving safety begins with an ASs ability to accurately perceive its surroundings. Perception failures of ASs have led to fatalities [2], including due to LiDAR-based perception [12]. However, it is particularly challenging to test LiDAR perception systems—a critical barrier as LiDAR is adopted by industry (e.g. [11], [13], [17]). Current testing techniques rely on large amounts of real world data, which is impractical due to the cost of collection and human labeling efforts leading to limited data, or simulation, which is limited in applicability by the simulation-reality gap [9], [10], [15]. This necessitates an approach that can provide novel, realistic data at a reasonable cost. Prior research has identified data augmentation as a method to diversify existing data sets; however, these techniques have focused on either diversity (e.g. [4], [5], [14], [16], [18]) or realism (e.g. [6], [8]) at the expense of the other. We address both realism and diversity at once by designing a set of mutation operations that increase test diversity, while also crafting a set of realism invariants that must hold during test generation. The final result is a set of novel and realistic test cases for LiDAR perception systems.

III. Implementation

Each mutation is implemented using Numpy [7], SemanticKITTI's developer tools [1], and open3D [19] Python libraries. The tool and all SUTs evaluated in the study are containerized in Docker for ease of replication.

The tool relies on the SemanticKITTI [1] data set as the basis for generating new test cases. However, the technique described in the paper is broadly applicable to any labeled LiDAR perception data set. To use a different data set, the tool must be adapted to its particular file format and labeling customs—we note that a consistent standard does not exist for either. For example, the SemanticKITTI data set has separate classes for the trunk of a tree and the tree's top, whereas the NuScenes [3] data set labels both as 'vegetation'. Such differences can impact the mutation operation, enforcement of realism invariants, and how SUTs are evaluated and transitioning to a different data set requires careful examination throughout the tool pipeline.

IV. Running the Artifact

A. Generating Tests

The `tool/` folder in the repository contains all of the tool source code. The `tool/tool_demo.sh` script runs a minimal example of the complete test generation pipeline. Initially, the script downloads a small subset of the SemanticKITTI data set and performs one-time processing to catalog available assets[1] Next, the script generates 5 test cases for each mutation; the script may be re-run to generate additional test cases. The perception systems tested reside in separate repositories; the tool repository contains additional instructions and scripts to automatically set up the SUTs.

B. Examining Study Results

The `study/` folder contains the code used to generate the tables and figures from the paper, as well as supplementary figures. The raw study results are publicly available[2]; the `study/generate_figures.sh` script downloads the study results and generates the figures and LaTeX-styled tables. The `study/README.md` file contains descriptions for each of the images produced and additional discussion about the parameters chosen for the study.

V. Requirements

The tool requires CUDA 10.0 support and was tested on Ubuntu 18.04. The shell (`.sh`) scripts provided to automate test execution are compatible with appropriate Unix shell environments. Tests were run on a pop-os 18.04 desktop with an Intel Xeon Silver 4216, 128GB of RAM, and an NVIDIA TITAN RTX GPU with 24GB of VRAM. The Docker environment files contain complete lists of all packages needed to run the tool and are automatically setup inside of the Docker container; if running outside of Docker, ensure that the appropriate packages are manually installed.

[1] To run on the full SemanticKITTI data set, the user must download and extract the data directly from the distributor: http://www.semantic-kitti.org/dataset.html. This is not included automatically due to the data set's size. Further instructions can be found in the repository.

[2] https://zenodo.org/record/7569212#.Y9P3KRzMK_4

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