Over Two Years of Challenging Environmental Conditions for Localization: The IPLT Dataset

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Abstract: This paper presents a new challenging dataset for autonomous driving applications: Institut Pascal Long-Term — IPLT — Dataset which was collected over two years and it contains, at the moment, 127 sequences and it still growing. This dataset has been captured in a parking lot where our experimental vehicle has followed the same path with slight lateral and angular deviations while we made sure to incorporate various environmental conditions caused by luminance, weather, seasonal changes.

1 INTRODUCTION

Autonomous driving applications are very critical and should be taken with absolute caution before deployment on public roads. Therefore, real-world data are needed in development, testing and validation phases. This paper presents a new dataset called IPLT (Institut Pascal Long-Term) dataset which mainly addresses localization under challenging conditions issues (snow, rain, change of season…).

Before explaining in details the composition of our dataset, it is important to explore the structure of an autonomous robot first. Figure 1 represents the operating mechanism of a general autonomous navigation platform in See-Think-Act cycle as explained in (Siegwart et al., 2011).

According to Figure 1, we can identify the four main modules interfering in this See-Think-Act mechanism:

- Perception of the environment and the state of the robot thanks to the different equipped sensors.
- Robot localization and mapping in the environment.
- Obstacle avoidance and trajectory planning.
- Processing and executing mission orders.

In our case, we are interested only in the first two modules which are directly dependant to the dataset presented in this paper. Our experimental vehicle acquires external environmental data through different

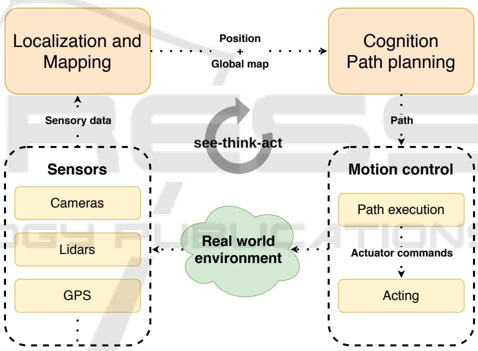

Figure 1: Autonomous driving platform represented in See-Think-Act Cycle (Siegwart et al., 2011).

equipped sensors (camera images, laser scans, GPS data, odometry data,...). Then, these sensory information are received by the localization and mapping (SLAM) module to allow the vehicle to interpret the environment so it can localize and update the map.

In our dataset, we repeatedly traverse the same parking lot, therefore, we managed to record many dynamic elements such as weather and lighting changes, seasonal changes, parking lot state changes (parked cars changes, empty parking lot, full parking lot, …), moving cars, moving pedestrians, …. In Figure 2, we present an overview of images showing some types of environmental conditions included in our dataset.

Our dataset is composed of 127 sequences in total and they are distributed as follows:

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(a) 2018-10-19-10-54-31 (b) 2018-10-22-19-40-27 (c) 2018-10-26-07-31-09 (d) 2018-10-26-09-11-01 (e) 2018-12-11-17-33-30

(f) 2018-12-13-10-36-57 (g) 2019-01-23-10-33-15 (h) 2019-01-23-16-05-30 (i) 2019-02-04-10-58-40 (j) 2019-10-01-16-54-55

(k) 2019-10-22-15-01-25 (l) 2019-12-05-16-43-56 (m) 2020-01-15-11-13-20 (n) 2020-01-31-16-07-34 (o) 2020-02-05-18-37-10

Figure 2: An overview of images recorded with the front camera for some sequences of our dataset. For each sequence we are indicating the acquisition date and symbolizing the environmental condition by a small icon. Please refer to Table 1 for more details about the designation of these condition icons.

Table 1: Designation of condition icons.

Icon	Designation
	Day & sunny condition
	Dusk condition
	Night condition
	Cloudy weather
	Rainy weather
	Fog condition
	Snow condition

- 22 sequences with sunny condition
- 43 sequences with cloudy weather
- 19 sequences with rainy weather
- 19 sequences with dusk condition
- 14 sequences with night condition
- 4 sequences with fog condition
- 5 sequences with snow condition
- 1 long sequence (`2019-12-05-16-43-56.bag`) recorded over one hour and 10 minutes with multiple loops in the parking lot starting from 16:44 until 17:54 and it incorporates day, dusk and night conditions.

We made our dataset public online in the hope of facilitating evaluations for researchers focusing on long-term autonomous navigation in dynamic environments. Our dataset can be downloaded through the link: http://iplt.ip.uca.fr/datasets/. Please enter the following username/password for a read-only access to our ftp server: ipltuser/iplt_ro.

The remainder of this paper is outlined as follows. Section 2 presents references of some related datasets, Section 3 provides information about the IPLT dataset and the equipment of our experimental shuttle which has been used to record it and Section 4 concludes the paper.

2 RELATED WORK

Intensive work on SLAM algorithms has produced a large number of related datasets such as Ford Campus Dataset (Pandey et al., 2011), Málaga Urban Dataset (Blanco-Claraco et al., 2014), Waymo Open Dataset (Sun et al., 2020),.... Some of these datasets were recorded in static environments with very little environmental changes, while some others are not revisiting a same location when recording different sequences. KiTTi (Geiger et al., 2013) is widely used dataset in SLAM applications, unfortunately, this dataset is not incorporating many environmental conditions since it was collected over one week (from 2011-09-26 to 2011-10-03). Later, a new dataset with a novel labeling scheme and data for 2D and 3D semantic segmentation was proposed in KiTTi 360 (Xie et al., 2016). However, this dataset consists of only 11 individual sequences and there is little overlap in trajectories between them.

Applications destined for autonomous driving and aiming for long-term localization uses must be evaluated on real-life scenarios where environment is changing over time. The VPRiCE challenge (Suenderhauf, 2015) is a dataset that offers some challenging cases for localization. Unfortunately, this dataset is offering only few sequences of some places that were revisited twice on different times. Similarly, the CMU Seasons dataset (Bansal et al., 2014) was acquired in urban and suburban environments totaling over 8.5 km of travel and contains 7,159 reference images and 75,335 query images acquired in different seasons. Sattler *et al.* (Sattler et al., 2018) have also presented a challenging dataset, called Aachen Day-Night, which incorporates 4,328 daytime images and 98 night-time queries. The NCLT (Carlevaris-Bianco et al., 2015), Oxford RobotCar (Maddern et al., 2017) and UTBM RobotCar (Yan et al., 2020) datasets are three widely used datasets for long-term tracking applications as they include different environmental conditions. The UTBM RobotCar dataset is including only few sequences (11 sequences in total) while in the two others, the traversed path is varied on each recording session.

In addition to environmental conditions, we are also interested in evaluating the effect of the lateral and angular deviation between sequences on the localization performance. However, the previously mentioned datasets do not provide sequences with such characteristics. This is the main reason that led us to record our own dataset and make it available to the community. Our dataset was used in our previous work (Bouaziz et al., 2021) to evaluate the impact of environmental changes and lateral and angular deviations on the localization performance.

3 IPLT DATASET

Our dataset contains currently 127 sequences collected over two years. In all the sequences, the vehicle has followed the same path, while in some of them, we made some slight lateral and angular deviations as specified in the Figure 3. All our sequences were recorded in the same direction and each one of them is about 200 m length.

Figure 3: Example of sequences recorded in a parking lot.

As specified in Figure 3, all the sequences in our dataset are forming loops in the parking lot. This makes from our dataset a very good asset for loop closure applications. All the sequences in our dataset were recorded with our experimental vehicle presented in Figure 4. It consists of an electric shuttle that is equipped with two cameras (front and rear), four LiDAR systems (two front and two rear), a consumer grade global positioning system (GPS). Each camera is recording gray-scale images with 10Hz frequency and both of them are having 100° FoV (Field of View).

The cameras were slightly moved in April 2019, so we have two different calibration settings, one for sequences recorded before April 2019 and one for more recent sequences. All the sequences are saved in rosbag files format and can be read by the ROS middleware (Quigley et al., 2009). The rosbag files contain the following rostopics:

- `/cameras/front/image`: front camera images.
- `/cameras/back/image`: rear camera images.
- `/robot/odom`: absolute poses calculated by wheel odometry.
- `/lidars/front_left/scan`: front-left lidar data.
- `/lidars/front_right/scan`: front-right lidar data.
- `/lidars/back_left/scan`: back-left lidar data.
- `/lidars/back_right/scan`: back-right lidar data.
- `/gps_planar`: GPS data.
- `/tf_static`: contains the extrinsic parameters of all sensors (cameras, lidars, GPS, ...).

In Table 2, we present the intrinsic parameters of our two cameras which are expressed in the unified camera model (Barreto, 2006). The unified camera model has five parameters: $[\gamma_x, \gamma_y, c_x, c_y, \xi]$ and they are used to project a 3D point $P(X_s, Y_s, Z_s)$ expressed in the Spherical coordinates into a 2D Point

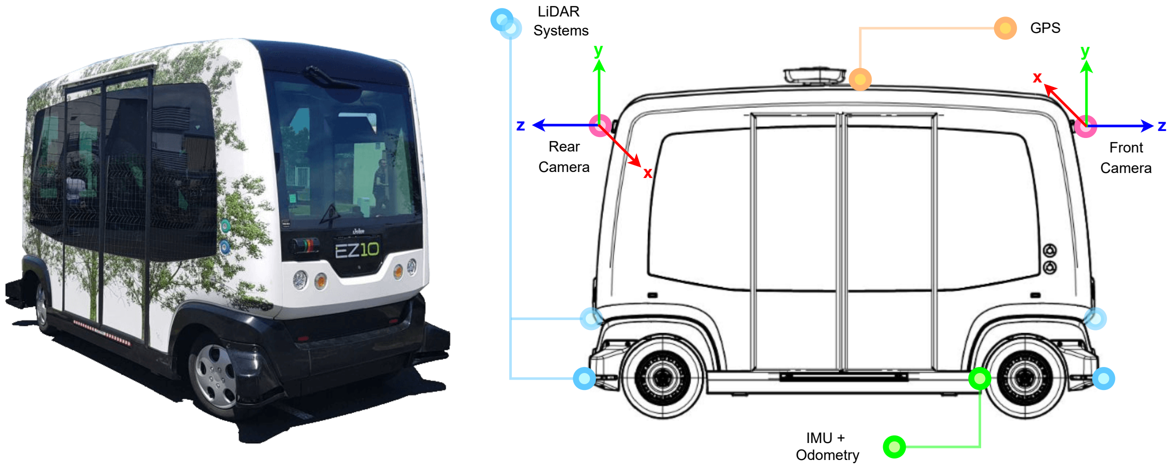

Figure 4: The EasyMile EZ10 electric shuttle used to record our dataset.

p_c expressed in the image plane as explained in Equation (1) and Figure 5.

Table 2: Intrinsic parameters of the cameras.

from_2018-10-19_to_2019-03-08					
	γ_x	γ_y	c_x	c_y	ξ
front	766.3141	769.5469	324.2513	239.7592	1.4513
back	763.5804	766.0006	326.2222	250.7755	1.4523

from_2019-10-01					
	γ_x	γ_y	c_x	c_y	ξ
front	770.0887	768.9841	330.3834	222.0791	1.4666
back	764.4637	763.1171	322.6882	247.8716	1.4565

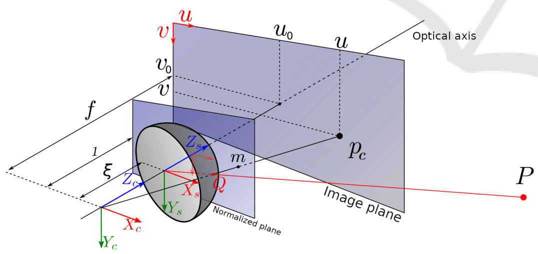

Figure 5: Unified camera model. A 3D point P is projected in the image plane of the camera into a distorted point p_c (Lébraly, 2012).

$$p_c = Km_c$$

$$K = \begin{bmatrix} f & 0 & u_0 \\ 0 & f & v_0 \\ 0 & 0 & 1 \end{bmatrix} \text{ and } m_c = \begin{bmatrix} \frac{X_s}{\rho} \\ \frac{Y_s}{\rho} \\ \frac{Z_s}{\rho} + \xi \end{bmatrix} \quad (1)$$

with $\rho = \sqrt{X_s^2 + Y_s^2 + Z_s^2}$ and $\xi = Z_c \geq 0$

Table 3 shows the extrinsic parameters of the cameras which are already integrated in the rosbag files. We have expressed the extrinsic parameters of the front camera in the coordinate system of the rear camera, this means that we present the translation and the rotation of the front camera with respect to the axis of the rear camera (see Figure 4). The rotations are presented in quaternions.

Table 3: Extrinsic parameters of the cameras.

from_2018-10-19_to_2019-03-08						
Rotation				Translation		
q_x	q_y	q_z	q_w	t_x	t_y	t_z
0.0030	-0.9998	0.01479	0.0123	-0.0304	-0.0698	-3.4635

from_2019-10-01						
Rotation				Translation		
q_x	q_y	q_z	q_w	t_x	t_y	t_z
0.0002	-0.9998	0.0200	0.0089	0.0600	-0.0321	-3.4637

For non ROS users, we provide a Python script (`extract_rosbag.py`) that can be used to extract images and odometry data from the rosbag files. This script takes as argument a list of rosbag files (one or more files) and generates a folder for each file as in the structure presented in Figure 6. Each folder contains a CSV (comma-separated values) file named `odometry.csv` and two sub-folders: `camera_back/` and `camera_front/`. The CSV file contains the absolute poses of the vehicle computed with the wheel odometry (8 entries for each pose: the translation t_x, t_y and t_z, the quaternion rotation q_x, q_y, q_z and q_w, and the corresponding timestamp in nanoseconds). The two folders `camera_back/` and `camera_front/` are containing the images of each corresponding camera and each image is named with its acquisition timestamp presented in nanoseconds.

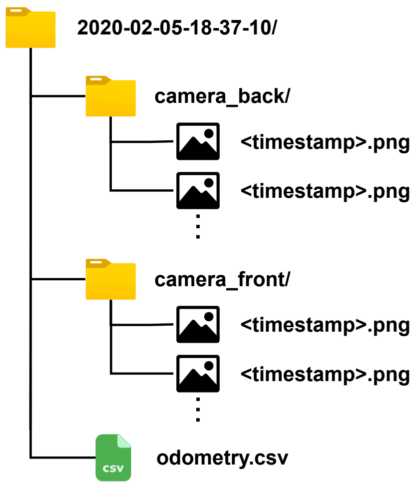

Figure 6: Structure of a folder generated by using the Python script (`extract_rosbag.py`) to extract the content of the rosbag file "`2020-02-05-18-37-10.bag`".

4 CONCLUSION

In this paper, we have presented a new dataset that contains challenging environmental conditions for long-term localization. This dataset was recorded over two years and it contains more than 100 sequences. We made our dataset available to the community in the hope that it will be useful to other researchers working in the field of long-term localization. This dataset was used in our previous works to evaluated the performance of different localization approaches in dynamic environments.

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