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Personal Information

Status:	**Undergraduate Student**
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RA Period:	**From 2017-02 to 2018-05**

Biography

I am about to join the MS robotics program at University of Pennsylvania. Before that, I was a research assistant in NYU Multimedia and Visual Computing Lab, advised by Professor Yi Fang. I am broadly interested in 3D Computer Vision, Pattern Recognition and Deep Learning.

Research Project: Accurate Vehicle Self-Localization in High Definition Map Dataset

1 Description

One of the biggest challenges in automated driving is the ability to determine the vehicle's location in realtime – a process known as self-localization or ego-localization. An automated driving system must be reliable under harsh conditions and environmental uncertainties (e.g. GPS denial or imprecision), sensor malfunction, road occlusions, poor lighting, and inclement weather. To cope with this myriad of potential problems, systems typically consist of a GPS receiver, in-vehicle sensors (e.g. cameras and LiDAR devices), and 3D High-Definition (3D HD) Maps. In this paper, we review stateof-the-art self-localization techniques, and present a benchmark for the task of image-based vehicle self-localization. Our dataset was collected on 10km of the Warren Freeway in the San Francisco Area under reasonable traffic and weather conditions. As input to the localization process, we provide timestamp-synchronized, consumergrade monocular video frames (with camera intrinsic parameters), consumer-grade GPS trajectory, and production-grade 3D HD Maps. For evaluation, we provide survey-grade GPS trajectory. The goal of this dataset is to standardize and formalize the challenge of accurate vehicle self-localization and provide a benchmark to develop and evaluate algorithms.

2 Method

In this section, we provide the details of the dataset contributed in this work. A HERE True car (shown in Figure.1) was sent to acquire data for this dataset. The acquisition vehicle was equipped with a well calibrated (intrinsic and extrinsic) HERE True platform that includes a Velodyne 32 LiDAR unit, high resolution cameras, and high precision positioning unit5 , which captures well-registered point clouds and street view imagery in world coordinates for high precision mapping purposes. Additionally, a consumer-grade dash camera was mounted on top of the windshield (above the roof of the vehicle) and roughly on the vehicle's major axis. A consumer-grade GPS receiver, was mounted closely be-

Figure 3: Side view of HERE True vehicle, with HERE True platform, consumer grade dash camera and GPS receiver.

Figure 1: Side view of HERE True vehicle, with HERE True platform, consumer grade dash camera and GPS receiver..

hind the camera (longitudinally), which leads to a potential longitudinal error and slight negligible altitudinal and lateral errors. Relative positions of the dash camera and GPS receiver are not given in the dataset. We believe this configuration simulates a realistic case to let researchers design a generalized solution to tackle this task.

3 Results

In this section, we conduct experiments to demonstrate the effectiveness of the proposed dataset. Different from the state-of-the-art self-location error evaluation metrics, which is represented in latitudinal/longitudinal angular distance or Euclidean distance in global coordinates, accurate in-map self-localization needs to be represented in ”road/map” coordinates. Given a ground truth trajectory, which is a set of discrete locations with time stamps, and consumer-grade GPS points P lla GPS (lla denotes WGS84 coordinate), find the previous and the next (timestamp-wise) ground truth points. Figure.2 shows the error statistics of each consumer grade GPS location versus its corresponding ground truth location. Grey, red, green, and blue shades represent absolute, lateral, longitudinal, and altitudinal errors respectively. The horizontal axis represents consumer

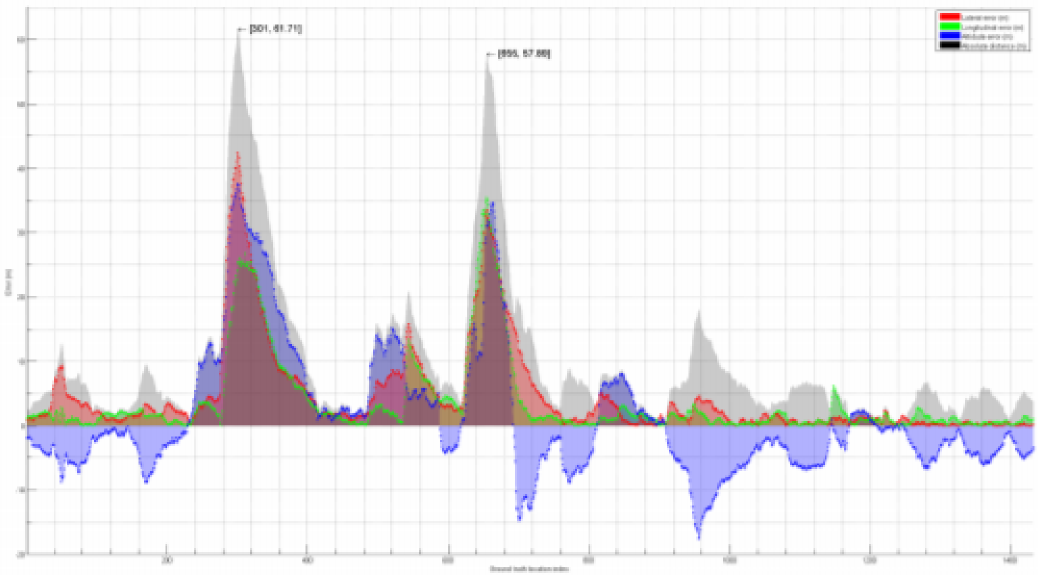

Figure 2: Error statistics of each consumer grade GPS location versus its corresponding ground truth location.

	$e_{lateral}$	$e_{longitudinal}$	$e_{altitudinal}$	$e_{absolute}$
Minimal (m)	*≈ 0*	*≈ 0*	*0.03*	*0.37*
Maximal (m)	*42.31*	*35.30*	*37.55*	*61.71*
Mean (m)	*4.74*	*3.67*	*6.97*	*9.88*
Median (m)	*1.74*	*1.33*	*4.70*	*5.93*
Standard deviation (m)	*7.5*	*6.42*	*7.32*	*11.75*

Table 1: Lateral, longitudinal and altitudinal error statistics along the entire dataset.

grade GPS sequence and the vertical axis represent error in meters. At image 301 and 655 the two largest errors can be observed due to complicated terrain. With proposed self-localization evaluation metric, we calculated lateral, longitudinal and altitudinal errors of each GPS point and its corresponding ground truth point, illustrated in Figure.2. The statistics are listed in Table 1. Absolute distance statistics are also given. Notice that all five values are calculated from absolute value of e