The SFU Mountain Dataset: Semi-Structured Woodland Trails Under Changing Environmental Conditions

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***Abstract*— We present a novel long-term dataset of semi-structured woodland terrain under varying lighting and weather conditions and with changing vegetation, infrastructure, and pedestrian traffic. This dataset is intended to aid the development of field robotics algorithms for long-term deployment in challenging outdoor environments. It includes more than 8 hours of trail navigation, with more available in the future as the environment changes. The data consist of readings from calibrated and synchronized sensors operating at 5 Hz to 50 Hz in the form of color stereo and grayscale monocular camera images, vertical and push-broom laser scans, GPS locations, wheel odometry, inertial measurements, and barometric pressure values. Each traversal covers approximately 4 km across three diverse woodland trail environments, and we have recorded under four different lighting and weather conditions to date: *dry*; *wet*; *dusk*; *night*. We also provide 383 hand-matched location correspondences between traversals as ground-truth for benchmarking place recognition and mapping algorithms. This paper describes the configuration of the vehicle, the trail environments covered, and the format of the data we provide.**

I. INTRODUCTION

The SFU Mountain Dataset has been recorded from a mobile ground-based robot (Figure 5) driving from the summit to the base of Burnaby Mountain, British Columbia, Canada, covering an altitude change of nearly 300 m (Figure 2). Sensors include color stereo cameras, monocular grayscale cameras, vertical and push-broom scanning laser rangefinders, GPS, wheel encoders, an inertial measurement unit, and a barometric pressure sensor.

The main purpose of the dataset is to provide comprehensive coverage of several types of semi-structured woodland trails under changing conditions (i.e. lighting, weather, vegetation, infrastructure, and pedestrians) in a highly self-similar natural environment. These data differ from most existing offerings such as the KITTI dataset [1], which covers structured urban environments targeted toward developing autonomous car technology. In contrast, we traverse challenging semi-structured woodland trails, resulting in data useful for evaluating place recognition and mapping algorithms (*i.e.* [2], [3]) across changing conditions in natural terrain.

The data, approximately 250 GB in size at this time, can be downloaded from `http://autonomylab.org/sfu-mountain-dataset`. We provide sensor data exported as JPEG images and CSV text files, and also the ROS bag files that were recorded directly from the robot. This paper describes the setup of the recording platform, the trail environments covered, and the format of the data.

(a) Trans-Canada Trail

(b) Powerline Trail

(c) Jim's Jungle Trail

Fig. 1: Three representative images from connected sections of the dataset that are very different in appearance.

II. Robot Setup

The configuration of our recording platform is illustrated in Figure 5:

- 2 × PointGray Firefly color cameras facing forward in stereo configuration with approximately 90° field of view (FMVU-03M2C-CS), 752 × 480 pixels, 1/3" Aptina MT9V022 CMOS, global shutter, 30 Hz
- 4 × PointGray Firefly monochrome cameras facing port, starboard, rear, and upward with approximately 90° field of view (FMVU-03M2M-CS), 640 × 480 pixels, 1/3" Aptina MT9V022 CMOS, global shutter, 30 Hz
- 1 × SICK LMS111 scanning laser rangefinder with 270° field of view in 0.5° increments, mounted with 180° roll and angled toward the ground in "push-broom" style approximately 20° to the horizontal, 18m range, 50 Hz
- 1 × SICK LMS200 scanning laser rangefinder with 180° field of view in 1° increments, sweeping a vertical plane normal to the x-axis of the robot, 8 m range, 10 Hz
- 1 × Garmin 18x GPS receiver with 15 m accuracy at 95 % confidence, 5 Hz
- 1 × UM6 inertial measurement unit providing orientation with 2° pitch and roll accuracy and 5° yaw accuracy, angular velocity and linear acceleration, 50 Hz
- Wheel encoders providing linear and angular velocity at 10 Hz
- Barometric pressure sensor from LG Nexus mobile phone in Pa at 30 Hz
- 4 × Titan 54 W off-road LED lights (ORBT9-54WD-FL) with brightness of 3780 lm, 5000 K color temperature and 60° beam angle, night sessions only

All cameras have exposure set to automatic, resulting in large shifts in effective brightness and in the amount of motion blur, which is significant in lower lighting. Color cameras are Bayer filtered, resulting in less detailed images than those from the grayscale cameras. During the night session, lights are mounted on the base plate below the two stereo cameras pointing outward at approximately 10° to the cameras' optical axes, as well as one light mounted above each side camera pointing in the port or starboard direction, covered with white tissue paper to improve light diffusion.

The robot was driven at its maximum speed of 1 m/s for most of the dataset, except for rough sections of Jim's Jungle.

III. Dataset

The dataset covers the traversal of three trails from the summit to the base of Burnaby Mountain, with a battery swap break approximately halfway through. We call the first and second halves of the data *part A* and *part B*, the start locations of which are marked in Figure 2. Histograms of sensor readings are shown in Figure 4 to summarize and compare the statistics of the two parts.

Part A includes the Trans-Canada Trail and approximately half of the Powerline trail, while part B consists of the rest of the Powerline trail and several hundred meters of Jim's Jungle trail. Recordings were made in four environmental conditions, which we refer to as *dry*, *wet*, *dusk*, and *night*.

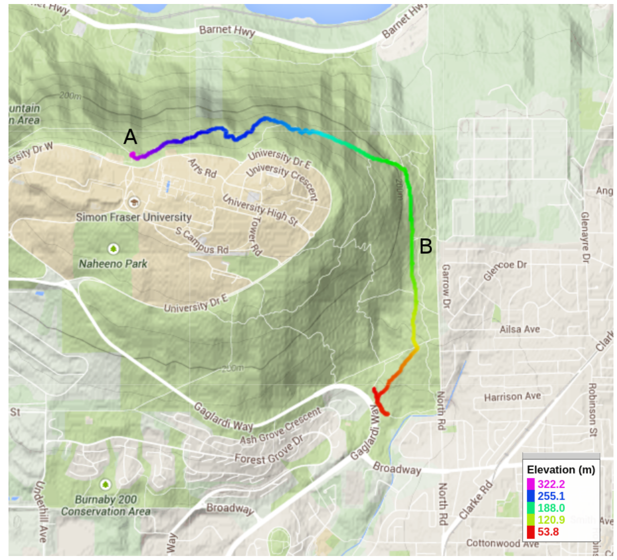


Fig. 2: GPS locations from the *dry* session, color coded by altitude. The start locations of the two continuous recordings A and B are labeled on the map. © 2015 Google, Inc.

A. Trail Environments

Each trail is significantly different in appearance to the others, as shown in Figure 1. The main features of each are described here.

Trans-Canada Trail: densely-forested mountainside terrain with a gray gravel path approximately 3 m wide. The starboard side of the path faces up the slope of the mountain, and is mostly dirt and small vegetation such as ferns and moss, with occasional tree trunks. The port side of the path faces down the slope, looking out on small vegetation and dense tall trees, with water and mountains in the distance. This section of the dataset covers an altitude change of approximately 125 m. The Trans-Canada Trail section consists of challenging and self-similar terrain, but distinctive natural and artificial landmarks are common.

Powerline trail: cleared woodland terrain on a gray and brown gravel path averaging 3 m wide, with low bushes and distant trees on both sides. This trail section includes powerlines, wooden power poles, and steel powerline towers. Most of this segment is oriented along the North-South cardinal axis. The Powerline trail is highly self-similar with few unique landmarks, and covers an altitude change of approximately 150 m.

Jim's Jungle: a section of trail at the base of Burnaby Mountain with dense tree cover and a narrow brown dirt path approximately 1 m wide. This segment has frequent turns, little altitude change, and an uneven trail surface that causes sharp orientation changes and occasional wheel slippage. On sunny days, shadows and bright patches are more common and more severe than in the other sections due to the dense canopy.

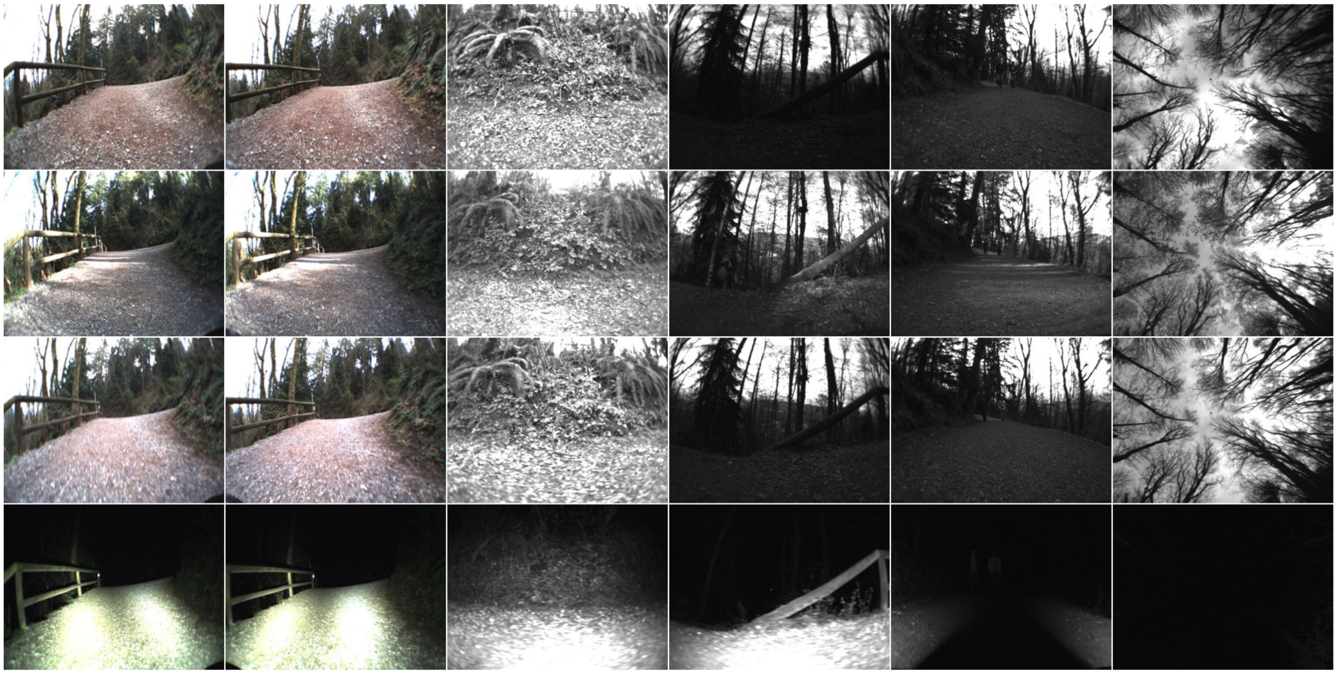


Fig. 3: A sample image from each camera on each session at one of the ground-truth matched locations. Images in each row belong to the same session; from top to bottom: *wet*, *dry*, *dusk*, *night*. Cameras from left to right: stereo left, stereo right, starboard, port, rear, upward.

B. Conditions

To date, we have recorded four sessions under different conditions:

- *dry*—recorded April 19, 2015 on a sunny day in good weather, with strong shadows and occasional severe light interference in the camera images.
- *wet*—recorded March 24, 2015 on a rainy day with overcast skies; shadows mild or nonexistent. The second half of part A contains a stop to attach an umbrella, which protects the vehicle from the rain and obscures the upward camera. The rain configuration of the vehicle is shown in Figure 7a.
- *dusk*—recorded April 2, 2015 on a dry overcast day just before sunset. The environment has an ambient brightness of approximately $400\,\mathrm{lx}$ at the beginning of part B, declining to nearly $30\,\mathrm{lx}$ by the bottom of the Powerline trail, and is almost zero lux in Jim's Jungle.
- *night*—recorded April 20, 2015 in dry weather, long after sunset. Bright off-road LED lights were mounted on the front and sides of the robot for this session to illuminate objects near to the robot, with brightness dropping off quickly beyond a distance of several meters. Figure 7b shows the vehicle on the Powerline trail at night.

C. Ground Truth Locations

In addition to the sensor data, we provide 383 ground-truth location matches between the four sessions: 237 from part A and 146 from part B. These are hand-aligned locations separated by approximately $10\,\mathrm{m}$ according to GPS readings, and provide a set of correspondences between the sessions by timestamp and sets of matching camera images. Envisioned uses include evaluating place recognition algorithms on known place matches, or for establishing known correspondences between localization and/or mapping systems over the different sessions. Figure 3 shows a single location from the Trans-Canada Trail recorded by each camera across all four conditions.

D. Sensor Calibration

We provide spatial transformations for each sensor in the form of a vector in $\mathbf{R}^6$, which represents x, y, z translation in meters and roll, pitch, yaw in radians with respect to the robot's origin as shown in Figure 5. Orientation is applied in the order of roll, then pitch, then yaw with respect to the fixed axes of the robot's coordinate frame. For cameras, we also provide intrinsic calibration in the form of a 3×3 camera matrix and 5-parameter plumb bob distortion model, in the form used by OpenCV.

We have synchronized sensor timestamps by measuring the rate of change of each sensor when the robot starts moving, and aligning the spikes representing this common event to the same time by a fixed offset. The timestamps of the bag files and in the CSV files already incorporate this offset, which is also stored in each sensor's `calibration.yaml` file for reference. The only sensors for which we cannot do this are the GPS and pressure sensors, which are fortunately also the least time-sensitive: neither pressure nor GPS location are as precise as the other sensors. Timestamps in the CSV files are given in nanoseconds since January 1, 1970.

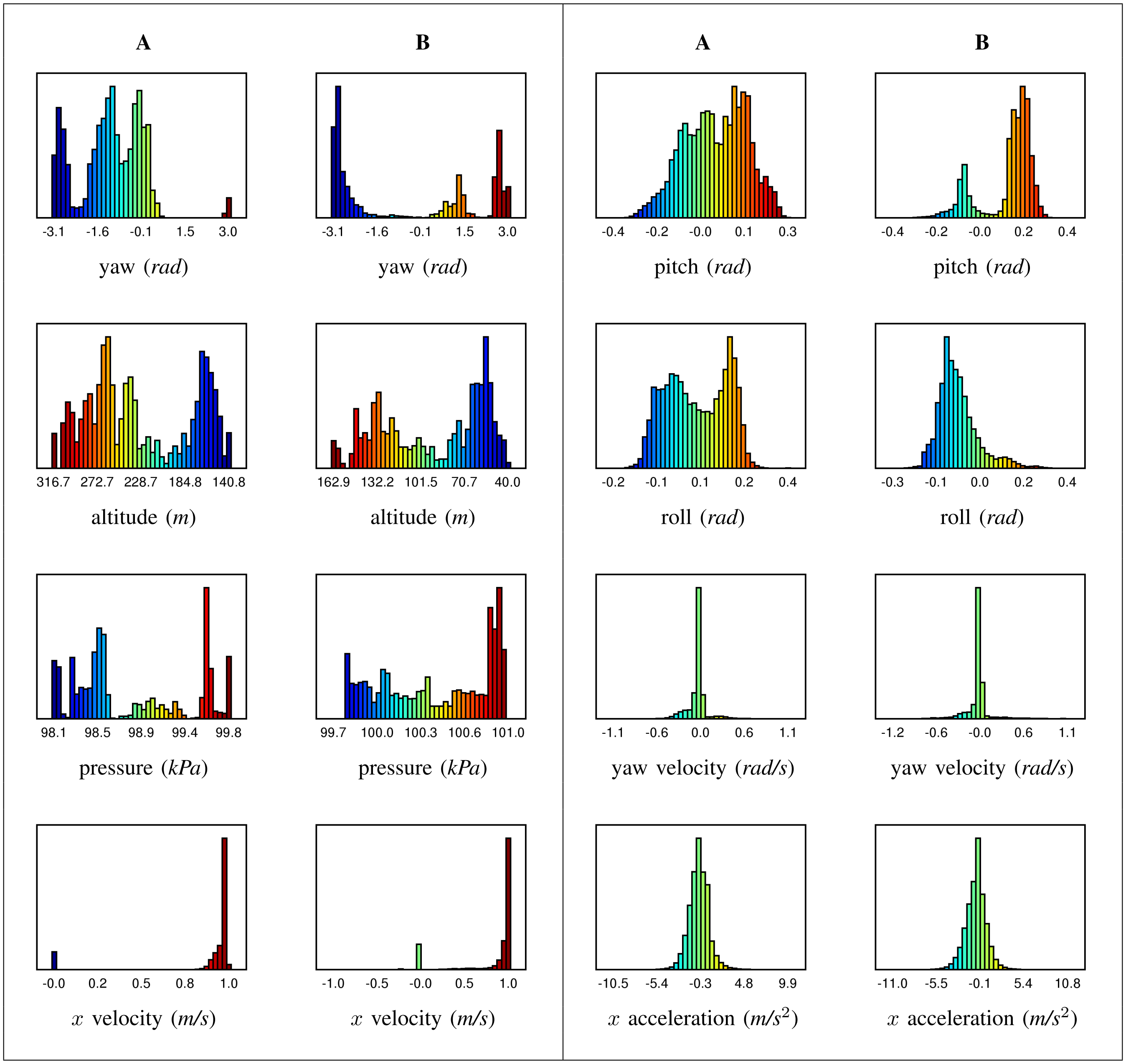


Fig. 4: Histograms of sensor data summarizing and comparing parts A and B of the trail sequence. Each histogram represents a quantity aggregated over all recording sessions. Pressure readings have a different offset depending on the weather, so we show the pressure for only the *dry* session. Yaw, pitch, roll and acceleration are read from the IMU; altitude comes from the GPS; pressure is measured by the Nexus phone; linear and angular velocity are given by wheel encoders.

Figure 6 shows readings of the trail surface from the front laser as colored by the stereo cameras, using the intrinsic and extrinsic calibrations provided, and registered according to unfiltered wheel odometry.

E. Data Format

Data is available in the form of JPEG image files, CSV text files and ROS bag files recorded directly from the vehicle. Parts A and B of the trail sequences are available as separate gzipped archive files <session>-<part>.tgz and bag files <session>-<part>.bag. The first line of each CSV file is a comma-separated header labeling each comma-separated field in the file. Images are located in a directory corresponding to their camera and are named by their timestamp: <camera>/<timestamp>.jpg.

In general, data are given in raw form except for the timestamp offset. However, we provide GPS locations in both (lat, long, alt) and (x, y, z) forms, with the latter given in meters in ENU (East-North-Up) coordinates with origin at the location of the first GPS location.

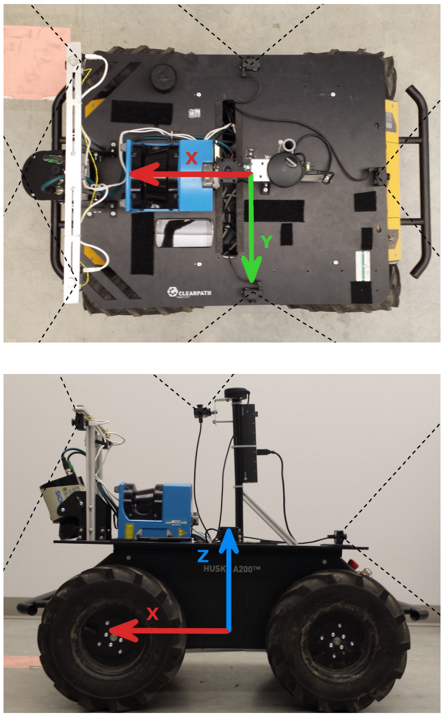


Fig. 5: Husky A200 platform used to gather the data in this paper, with arrows indicated the axes of the robot's coordinate frame and dotted lines indicating approximate fields of view of the cameras.

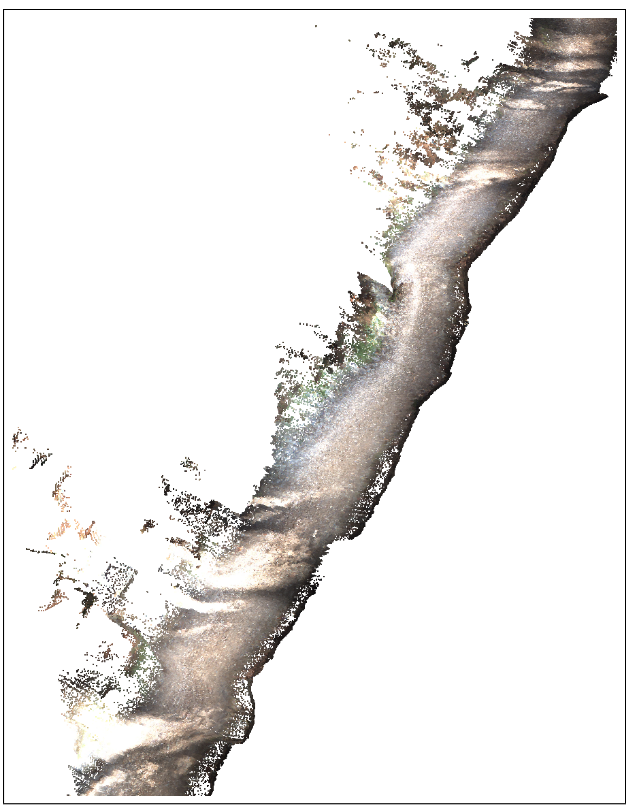
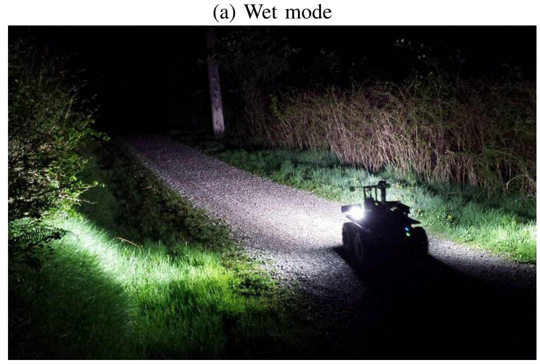


Fig. 6: Trail surface as scanned by the front laser, colored by projecting into the cameras and registered by unfiltered wheel odometry.

(a) Wet mode



(b) Night mode

Fig. 7: Configurations of the robot for two of the environmental conditions in the dataset.

IV. Summary and Future Work

We have presented a calibrated, synchronized, and ground-truth-aligned dataset of woodland trail navigation in semi-structured and changing outdoor environments. The data are highly challenging by virtue of the self-similarity of the natural terrain; the strong variations in lighting conditions, vegetation, weather, and traffic; and the three highly different trails. In the future we will expand this dataset by recording more traversals in different conditions. Notable desired conditions are mid-summer vegetation growth, autumn leaf colors, bare trees in winter, and the rare Burnaby winter snow. We also plan to obtain aerial footage of the same trails as captured by a UAV following the GPS locations recorded by the ground-based robot.

Acknowledgement

Thanks to Jacob Perron, Shokoofeh Pourmehr, Lingkang Zhang, and Jack Thomas. This work was supported by the Natural Sciences and Engineering Research Council (NSERC) through the NSERC Canadian Field Robotics Network (NCFRN).

References

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