An Off-Road Terrain Dataset Including Images Labeled with Measures of Terrain Roughness

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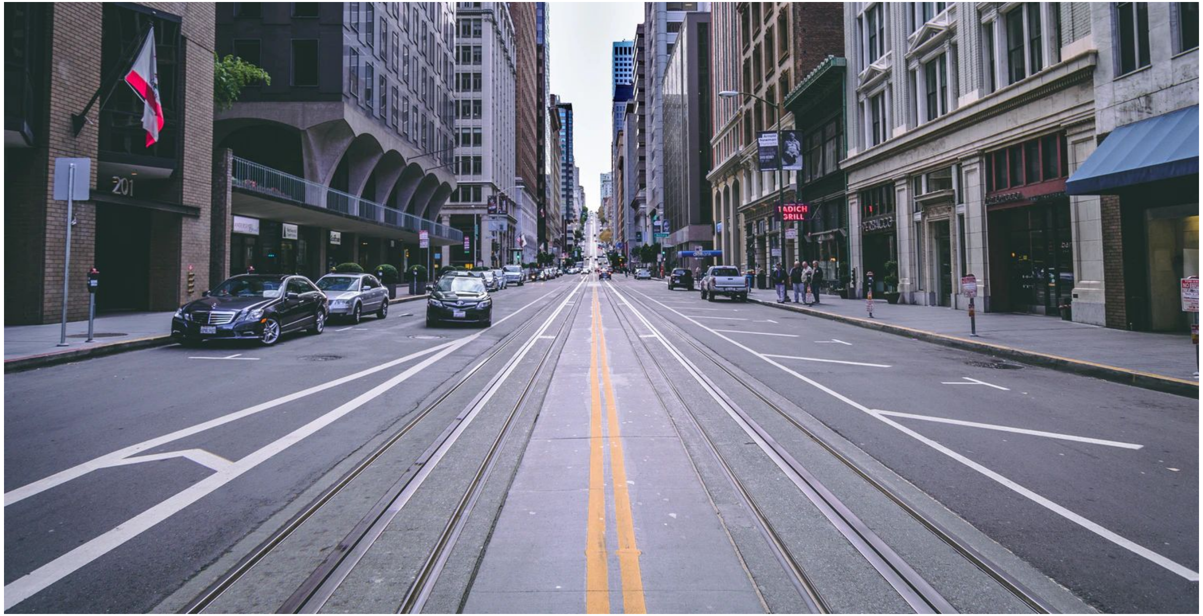
Motivation

A **current goal** of the self-driving vehicle industry is **Level 4 autonomy**, or complete autonomy in specific conditions (i.e. **smooth**, **marked** terrain).



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Motivation

Level 5 Autonomy

- Routes may include unmarked or unpaved terrain

Autonomous Ground Vehicles

- Designed to handle specific tasks [3]
- Search and rescue, mining [4, 5], planetary exploration [6]

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It is crucial for autonomous vehicles to understand off-road terrain roughness.

This research

1. Dataset designed to enable autonomous vehicles to learn about off-road terrain using a single, monocular image

2. Eight roughness labeling schemas derived from IMU z-axis acceleration for labeling the images in the dataset

Challenges

Challenges

1. Lack of relevant off-road terrain data
2. Traversing rough off-road terrain can cause an unsteady camera
3. Labeling images with a single, quantitative measure of roughness derived from IMU z-axis acceleration readings is hard

Solution

- Collected an **off-road terrain dataset**
- Derived and evaluated eight **roughness labeling schemas** for the images in our dataset

Dataset

Data collection and preparation

Mountain bike with sensors

- Dual GPS receivers
- Dual high resolution IMU’s
- Camera synchronized to both accelerometers
- Strain-gauge based power meter
- Wheel rotation speed sensor

Percy Warner Park

- Nashville, TN
- Late July - early October 2020

Data collected

- Video data
- Sensor data

In total, we collected 12,982 images covering nearly 44 miles of terrain

Sample images

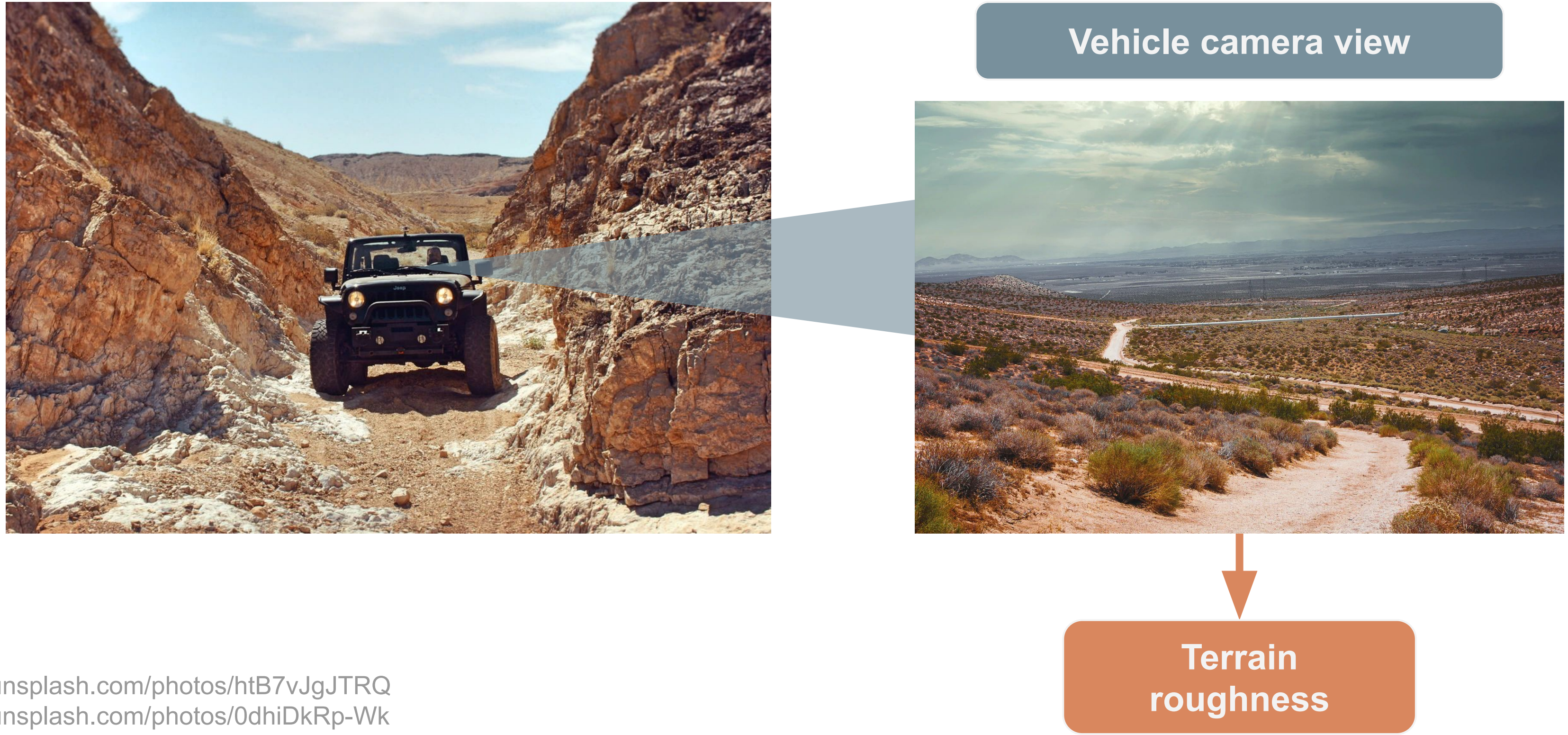
Sensor data

For each data collection session:

1. **accelerometer_calibrated_split.csv:** Calibrated and uncalibrated acceleration readings from the accelerometer
2. **gyroscope_calibrated_split.csv:** Calibrated and uncalibrated readings from the gyroscope
3. **magnetometer_split.csv:** Uncalibrated magnetometer readings
4. **gps.csv:** Latitude, longitude, altitude, speed, heading, velocity
5. **record.csv:** Latitude, longitude, distance traveled, speed, altitude
6. **Roughness labeling CSVs:** 8 potential roughness labels for each image

Roughness Labels

Roughness labels



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Roughness Metric

Standard deviation of a **1-second sampling** of **z-axis acceleration** readings.

- Describes entirety of terrain
- Accounts for cases where the mean is not 0

Labeling Images

- At what timestamp should this sampling be taken?
- How should we discretize this roughness metric?

At what timestamp should this sampling be taken?

Considered 2 **Terrain Sampling Methods (TSMs):**

TSM 1 — Centered around 5 meters ahead of the image

TSM 2 — Directly ahead of the image

How should we discretize the roughness metric?

Original groups	4 discrete groups determined with data visualization
k = 2 groups	k-means clustering with k = 2
k = 3 groups	k-means clustering with k = 3
k = 4 groups	k-means clustering with k =4

Labeling schemas

Label 1

TSM 1
Original groups

Label 2

TSM 1
k = 2 groups

Label 3

TSM 1
k = 3 groups

Label 4

TSM 1
k = 4 groups

Label 5

TSM 2
Original groups

Label 6

TSM 2
k = 2 groups

Label 7

TSM 2
k = 3 groups

Label 8

TSM 2
k = 4 groups

Image validation

- There was sufficient data for labeling images
- This data met certain criteria
  - Continuity, nonzero speed, etc....

- The image contained a clear, visible path




Method

1) Trained **roughness classifiers** for each of the 8 labels
2) **Evaluated** each on a selection set
3) Chose the **two labeling schemas** corresponding to the models with the best performance

Sample labeled images

Performance (selection set)

	TSM 1		TSM 2	
	Overall accuracy	**Avg class accuracy**	**Overall accuracy**	**Avg class accuracy**
Original groups	34.75%	36.48%	45.48%	47.72%
k = 2 groups	71.19%	71.33%	73.45%	75.06%
k = 3 groups	55.65%	46.20%	60.17%	52.30%
k = 4 groups	45.76%	35.72%	50.00%	46.27%

Selected labeling schemas evaluated on the test set

1. **Label 6** (TSM 2, k = 2 groups)

   Overall accuracy: 69.91%

   Average accuracy by class: 66.17%

2. **Label 8** (TSM 2, k = 4 groups)

   Overall accuracy: 51.32%

   Average accuracy by class: 34.73%

Chronological Split

- First 70% of each session: Training
- Next 15%: Validation
- Final 15%: Testing

Performance (on respective test sets)

Labeling schema	**Split**	**Overall accuracy**	**Avg class accuracy**
Label 6	Random	69.91%	66.17%
Label 6	Chronological	70.19%	67.44%
Label 8	Random	51.32%	34.73%
Label 8	Chronological	52.92%	39.93%

Lessons Learned

Lessons Learned

- Data for off-road autonomous vehicles can be **collected at scale** by **small, agile, and durable vehicles operated by humans**
- We can learn about the **future kinetics of the vehicle** as a result of upcoming terrain roughness from a **single, monocular image**

Future Work

Future work

Expand geographic region for data collection

Collect data from other sensors or vehicles

Roughness metric accounting for all visible terrain in an image

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References

[1] Darrell Etherington, “Over 1,400 self-driving vehicles are now in testing by 80+ companies across the us,” Jun 2019.
[2] NHTSA, “Automated vehicles for safety,” Jun 2020, Available: https://www.nhtsa.gov/technology- innovation/automated-vehicles.
[3] S. George Fernandez, K. Vijayakumar, R Palanisamy, K. Selvakumar, D. Karthikeyan, D. Selvabharathi, S. Vidyasagar, and V. Kalyanasundhram, “Unmanned and autonomous ground vehicle,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 9, no. 5, pp. 4466, 2019.
[4] Akhil Kurup, Sam Kysar, and Jeremy P. Bos, “SVM based sensor fusion for improved terrain classification,” *Autonomous Systems: Sensors, Processing, and Security for Vehicles and Infrastructure 2020*, 2020.
[5] Mingliang Mei, Ji Chang, Yuling Li, Zerui Li, Xiaochuan Li, and Wenjun Lv, “Comparative study of different methods in vibration-based terrain classification for wheeled robots with shock absorbers,” *Sensors*, vol. 19, no. 5, pp. 1137, 2019.
[6] NASA, “Mars 2020 Perseverance Rover,” 2020, Available: https://mars.nasa.gov/mars2020.
[7] Hendrik Dahlkamp, Adrian Kaehler, David Stavens, Sebastian Thrun, and Gary Bradski, “Self-supervised monocular road detection in desert terrain,” *Robotics: Science and Systems II*, 2006.
[8] David Stavens and Sebastian Thrun, “A self-supervised terrain roughness estimator for off-road autonomous driving,” *arXiv:1206.6872*, 2006.
[9] Vivekanandan Suryamurthy, Vignesh Sushrutha Raghavan, Arturo Laurenzi, Nikos G. Tsagarakis, and Dimitrios Kanoulas, “Terrain segmentation and roughness estimation using rgb data: Path planning application on the centauro robot,” *2019 IEEE-RAS 19th International Conference on Humanoid Robots (Humanoids)*, 2019.
[10] Yumi Iwashita, Kazuto Nakashima, Adrian Stoica, and Ryo Kurazume, “TU-Net and TDeepLab: Deep learning-based terrain classification robust to illumination changes, combining visible and thermal imagery,” *2019 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR)*, 2019.
[11] Christian Weiss, Hashem Tamimi, and Andreas Zell, “A combination of vision- and vibration-based terrain classification,” *2008 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2008.

References (continued)

[12] Chengchao Bai, Jifeng Guo, and Hongxing Zheng, “Three-dimensional vibration-based terrain classification for mobile robots,” *IEEE Access*, vol. 7, pp. 63485–63492, May 2019.

[13] Christian Weiss, Holger Frohlich, and Andreas Zell, “Vibration-based terrain classification using support vector machines,” *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2006.

[14] Garmin Developers, “FitCSVTool,” Available: https://developer.garmin.com/fit/fitcsvtool.

[15] Garmin Developers, “FIT protocol,” Available: https://developer.garmin.com/fit/protocol.

[16] Shastri Ram, *Semantic Segmentation for Terrain Roughness Estimation Using Data Autolabeled with a Custom Roughness Metric*, Ph.D. thesis, Carnegie Mellon University, 2018.

[17] fastai, “fastai v1 documentation,” Available: https://fastai1.fast.ai.

[18] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, “Deep residual learning for image recognition,” *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.

[19] fastai, “vision.transform,” Available: https://fastai1.fast.ai/vision.transform.html#Data- augmentation.

Thank you.

Questions