

GROUND PLANE TO GRADING

A TERRAIN FEATURE PERCEPTION BASELINE FOR AUTONOMOUS MOTOR GRADING IN MINING

SINA QAHREMANI, KEYVAN HASHTRUDI-ZAAD, JOSHUA A. MARSHALL
INGENUITY LABS RESEARCH INSTITUTE AT QUEEN'S UNIVERSITY

ICRA™
IEEE INTERNATIONAL CONFERENCE
ON ROBOTICS AND AUTOMATION

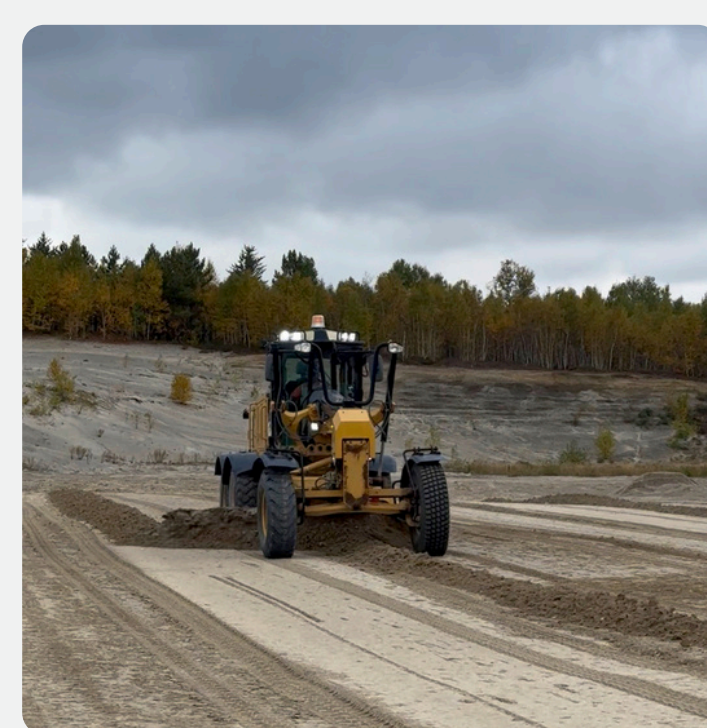
2026
VIENNA

1 WHY AUTONOMOUS GRADING?

- **Haul roads** are a mine's circulatory system — every **1%** increase in **rolling resistance** cuts truck **speed** by **10%** and raises **fuel costs** by **2–3%** [1].
- Graders rank among the **deadliest mobile mining equipment**. Operators face silica **dust**, extreme **heat**, and chronic **fatigue** — a task in which human **attention** degrades rapidly.
- **Skilled grader operators** are critically scarce (only **40%** are adequately trained), yet grading is one of the most **skill-intensive operations** in mining.



Cutting



Spreading

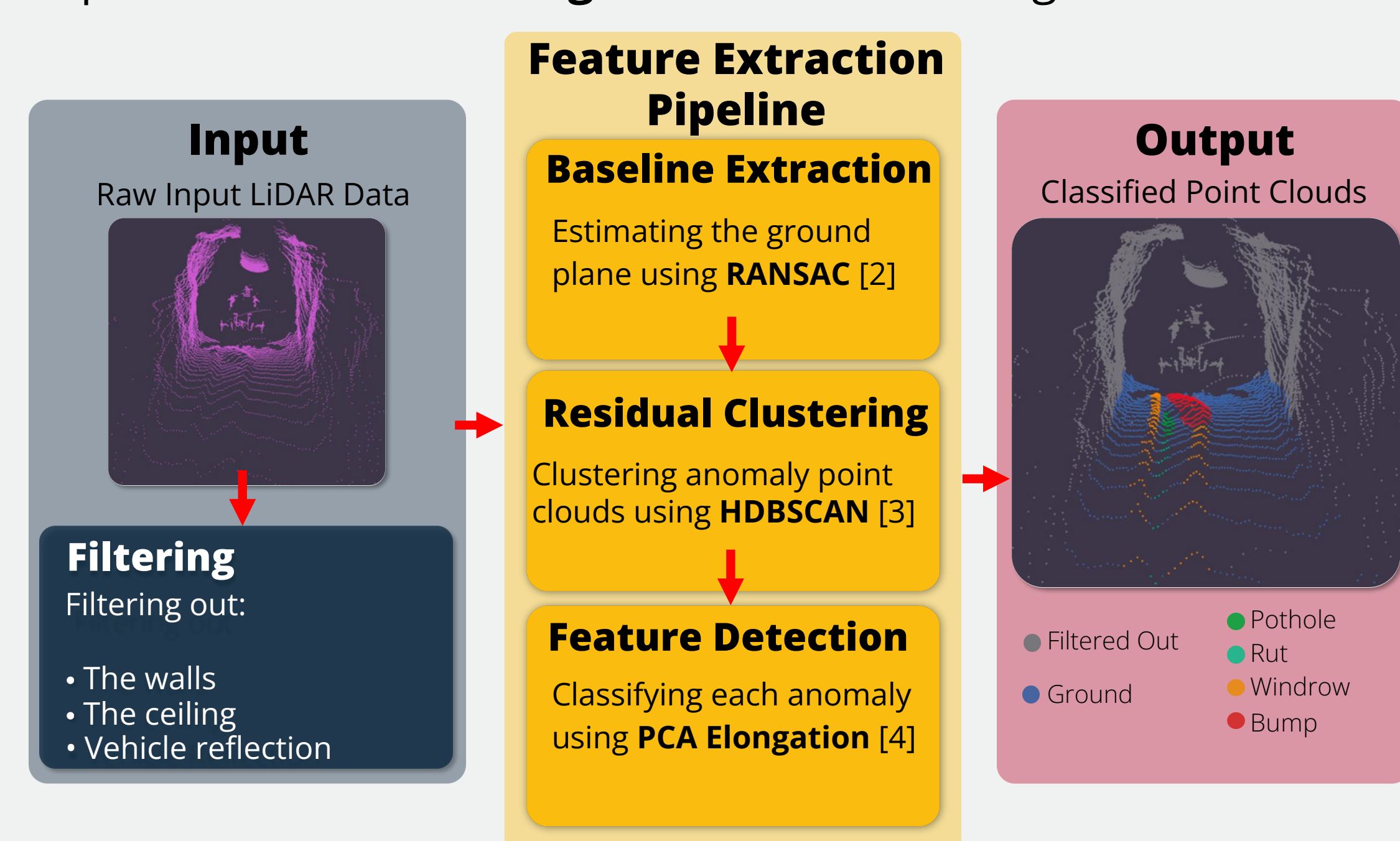


Ditching

Training Site — Canada

3 FEATURE PERCEPTION

Reliable perception is the foundation of autonomous grading — this work presents a **baseline algorithm** toward that goal.

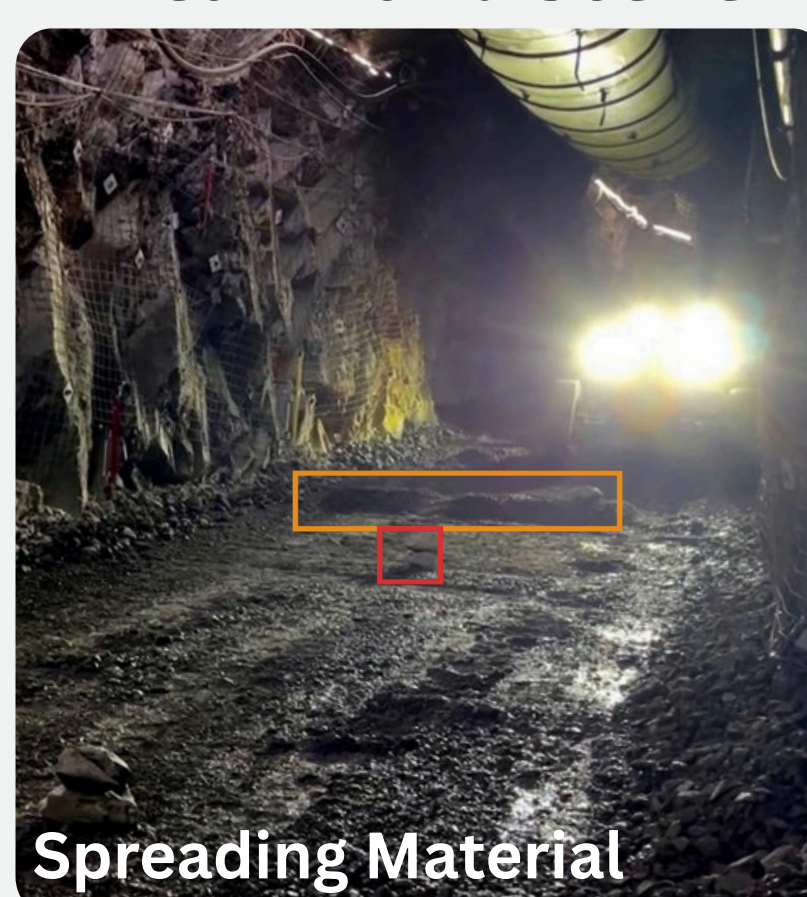


5 FIELD TRIALS

Multiple **grading scenarios** were performed underground at **Ducky Mine**. Two representative **examples** are shown here:

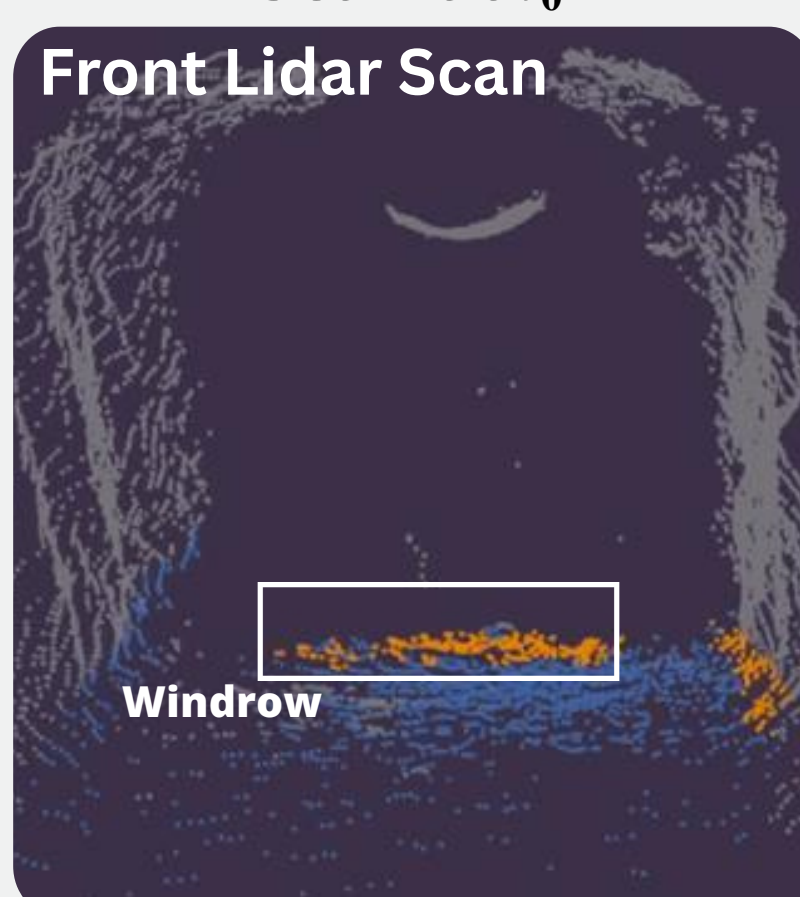
Classified LiDAR Point Cloud

Real-World Scene



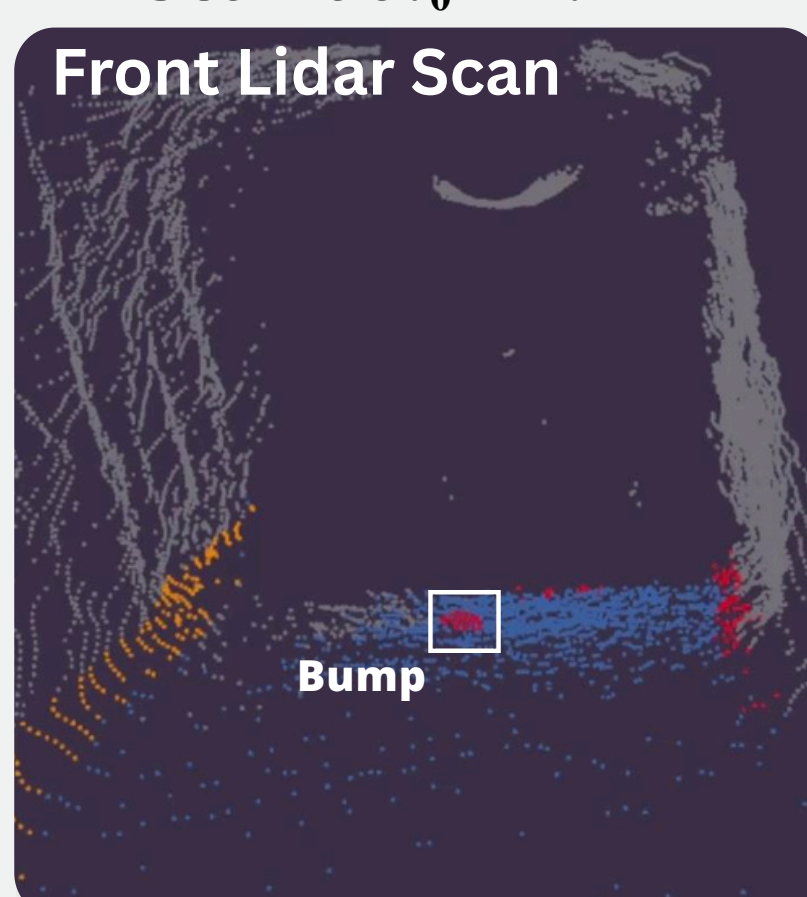
Spreading Material

Scan at t_0



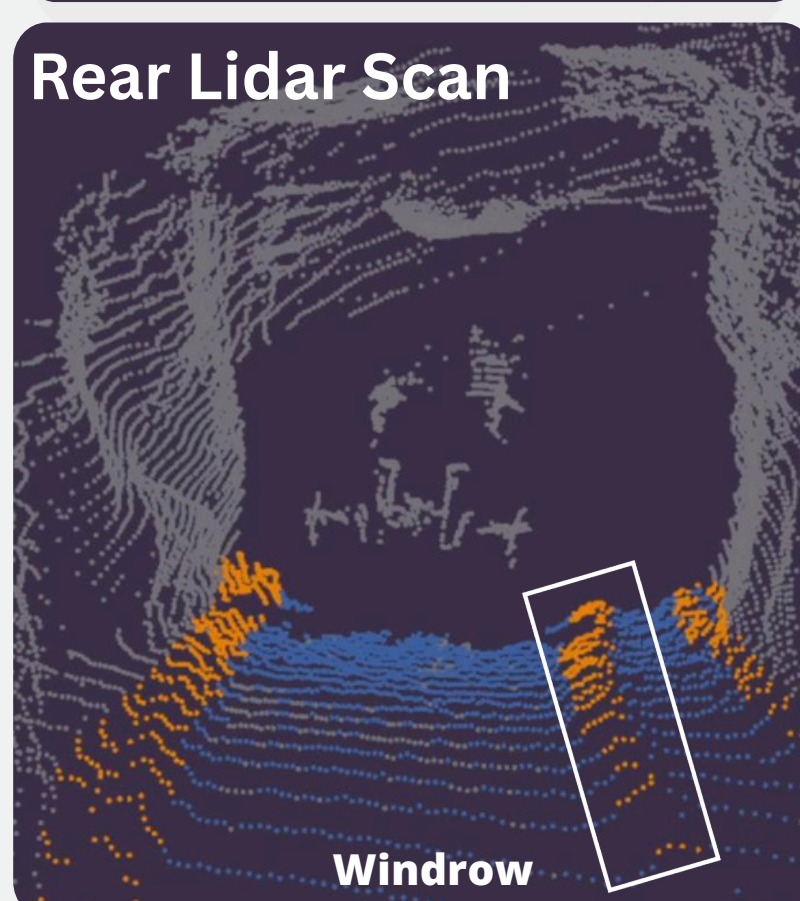
Windrow

Scan at $t_0 + \Delta t$

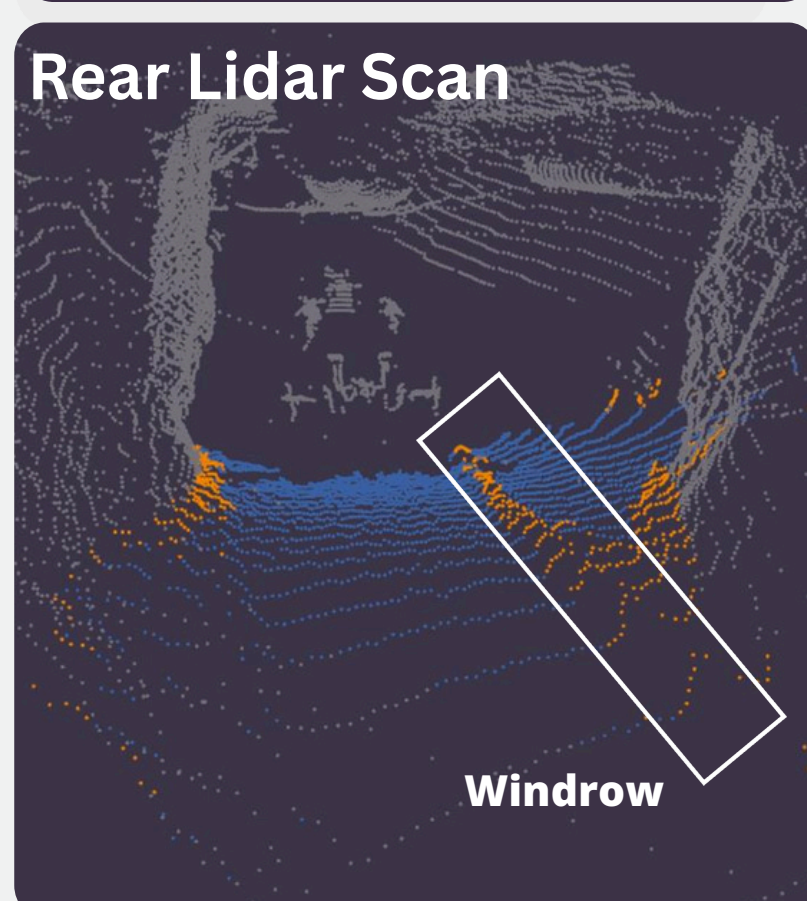


Bump

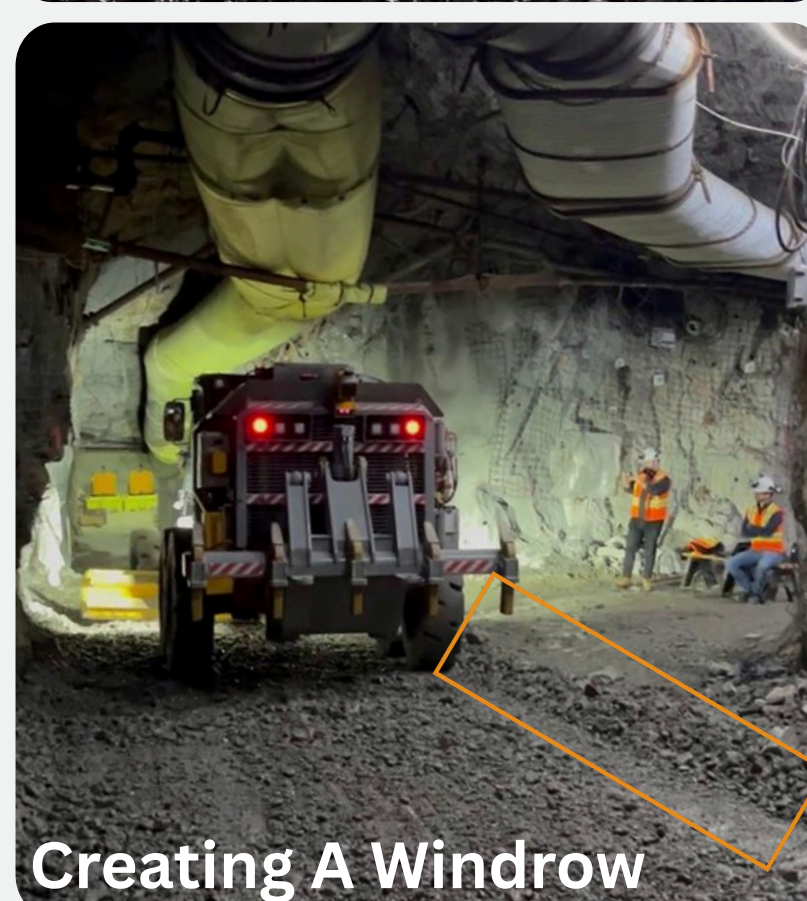
Rear Lidar Scan



Windrow



Windrow



Creating A Windrow

Test Mine — Canada

ACKNOWLEDGEMENTS

This work is supported by Mitacs Accelerate. The authors thank Algoryx Simulation AB for providing a complimentary license for AGX Dynamics. Field experiments took place on the Robinson-Huron Treaty territory and the traditional lands of the Atikameksheng Anishnawbek and Wahnapiatae First Nation.



2 THE HARDWARE

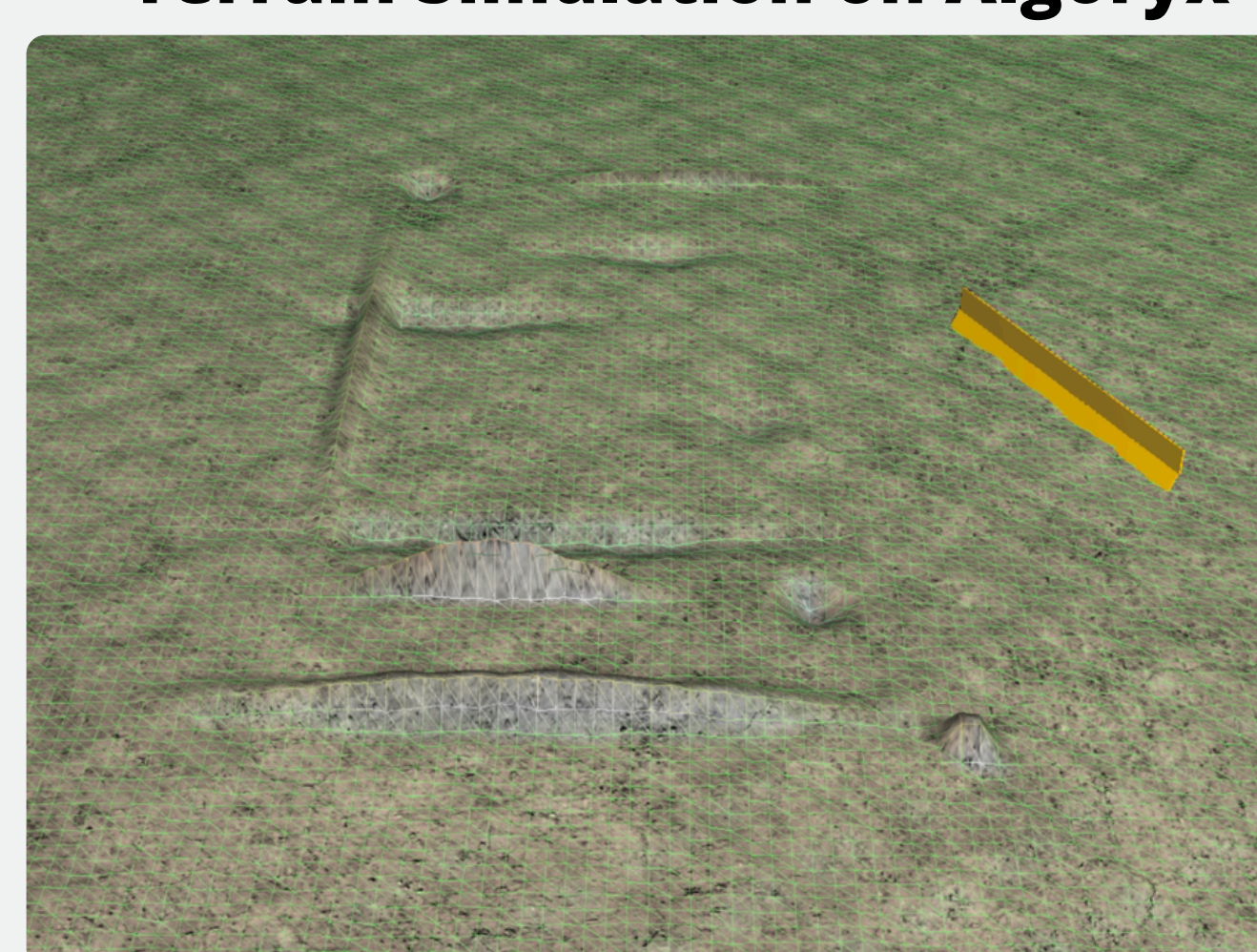
- Purpose-built for **mining**
- Mechanically complex: **articulated** center frame, front-wheel **steering** with **lean** control, **6 DoF blade (moldboard)**
- Equipped with three **Ouster OS0-32** LiDARs: **Front, Rear, Moldboard-facing**
- LiDAR data published via **ROS 2** at **20 Hz**



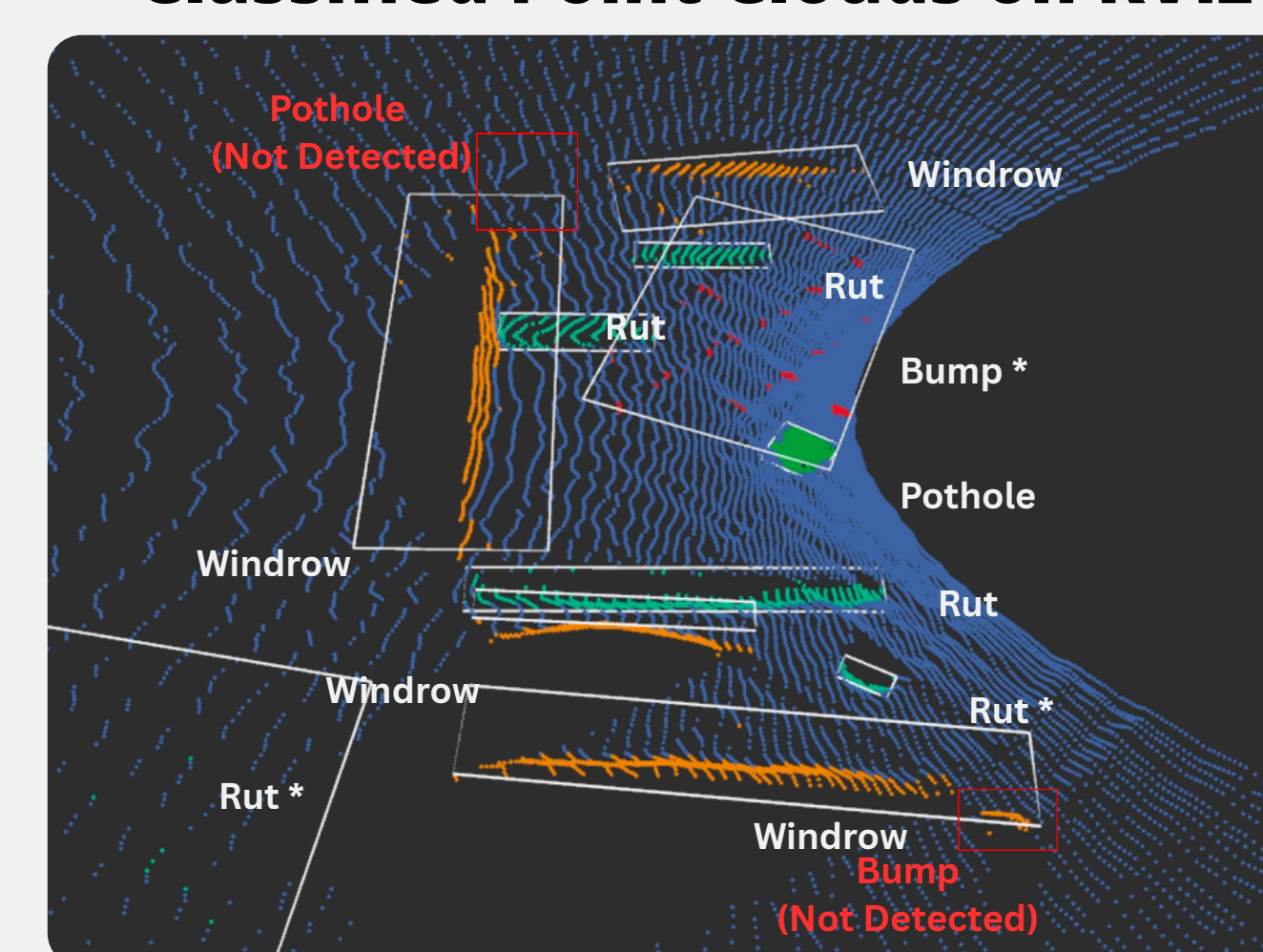
R&D Facility — Canada (Vehicle is altered by GPT Image 1.5 for confidentiality purposes)

4 PRE-FIELD TRIAL EVALUATION

Terrain Simulation on Algoryx



Classified Point Clouds on RViz



* Wrong Prediction

100 randomized scenarios were generated, and the algorithm was evaluated in **two configurations**: with and without **multi-frequency surface roughness** applied to the ground plane.

Without Ground Roughness

Overall accuracy: $90.9 \pm 5.0\%$

True class	Predicted class				
	Ground	Pothole	Rut	Windrow	Bump
Ground	99.8%	<1%	<1%	<1%	<1%
Pothole	52.3%	31.5%	16.1%	<1%	<1%
Rut	48.9%	2.0%	48.8%	<1%	<1%
Windrow	32.7%	<1%	<1%	57.7%	9.5%
Bump	36.7%	0	<1%	12.1%	51.2%

With Ground Roughness

Overall accuracy: $89.6 \pm 6.3\%$

True class	Predicted class				
	Ground	Pothole	Rut	Windrow	Bump
Ground	98.8%	<1%	<1%	<1%	<1%
Pothole	50.3%	36.3%	13.4%	<1%	<1%
Rut	46.4%	4.0%	49.2%	<1%	<1%
Windrow	34.2%	<1%	<1%	52.1%	13.5%
Bump	35.3%	0	<1%	9.6%	55.1%

6 DISCUSSION

Summary: This work establishes a **baseline geometric algorithm** for terrain feature detection for a real motor grader. Algorithm accuracy was evaluated quantitatively in simulation only; collecting **ground-truth annotations** during future field campaigns and creating semantic labels for point clouds are necessary to validate real-world performance.

Challenges:

- The **curved tunnel walls** along both sides of the vehicle are not fully removed by the filtering step, causing persistent **false positives misclassified** as windrows or bumps.
- The **front LiDAR mounting angle** was not optimal, producing sparse, **noisy point density** that degrades detection of smaller features.
- LiDAR streams recorded over Ethernet to a laptop suffered **packet loss** and dropped frames, causing **data dropout**; direct recording onto an **onboard NVMe SSD** and using ROS2 bag **MCAP** rather than **SQLite3** are necessary for reliable capture.

Future Work: This work benchmarks future ML methods for small-feature recall. **Registering** front and rear scans will enable before/after surface comparison for **grading quality** assurance. Detected features will ultimately feed a **closed-loop moldboard controller**.

REFERENCES

- [1] Mining Engineering, "How Does Poor Haul Road Design Affect Fuel Consumption and Equipment Maintenance?," Mining Doc, 2026.
- [2] M. Fischler & R. Bolles, "Random Sample Consensus," Commun. ACM, 24(6), 1981.
- [3] R. Campello, D. Moulavi & J. Sander, "Density-Based Clustering Based on Hierarchical Density Estimates," PAKDD, 2013.
- [4] M. Weinmann, B. Jutzi & C. Mallet, "Semantic Point Cloud Interpretation Based on Optimal Neighborhoods, Relevant Features and Efficient Classifiers," ISPRS J. Photogramm. Remote Sens., 105, 2015.