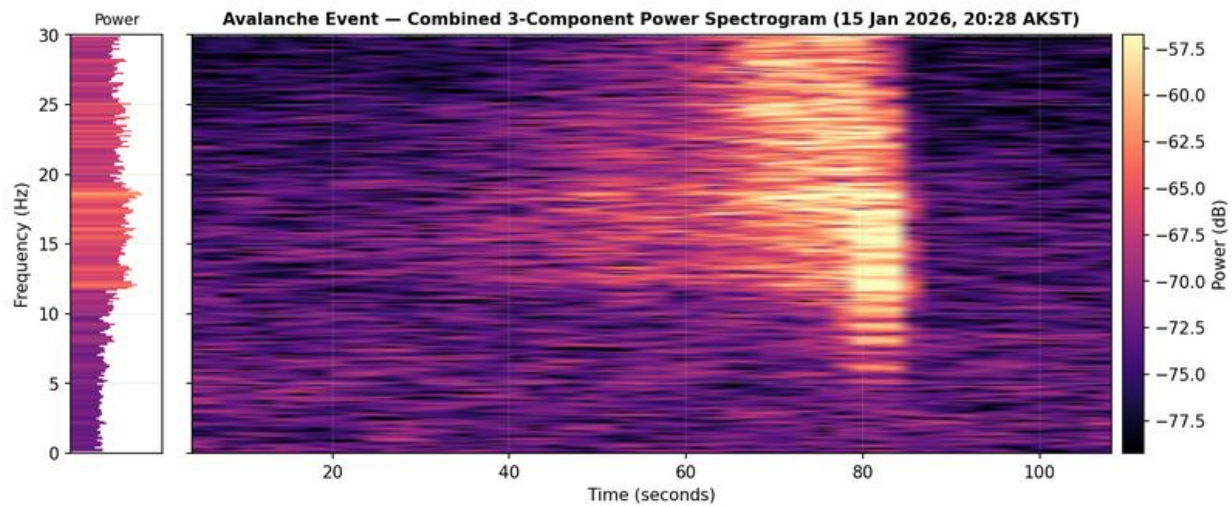




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Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.	
4. Title and Subtitle		5. Report Date	
		6. Performing Organization Code	
7. Author(s)		8. Performing Organization Report No.	
9. Performing Organization Name and Address		10. Work Unit No. (TRAIS)	
		11. Contract or Grant No.	
12. Sponsoring Agency Name and Address		13. Type of Report and Period Covered	
		14. Sponsoring Agency Code	
15. Supplementary Notes			
16. Abstract			
17. Keywords		18. Distribution Statement	
19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price

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Executive Summary

Three Viotel accelerometers were deployed along the Turnagain Arm corridor near Girdwood, Alaska. The objective was to determine whether inexpensive ultra-low-noise sensors can automatically detect and classify avalanches in a noisy transportation corridor shared with the Alaska Railroad and Seward Highway.

Over 145 days of continuous monitoring, the sensors recorded 400 seismic events from trains, earthquakes, sensor artefacts, and one confirmed avalanche. A hybrid classification algorithm was developed that achieves 94.7% cross-validated accuracy on labeled events and correctly identifies the confirmed avalanche.

The avalanche signal has a distinctive signature — low spectral centroid, very high crest factor, gradual onset — that separates it clearly from trains and earthquakes. However, with only one confirmed avalanche recorded, the detection algorithm cannot yet be statistically validated. A second year of monitoring is recommended to collect additional avalanche examples.

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Introduction

The Problem

Avalanches threaten the Seward Highway and Alaska Railroad through the Turnagain Arm region. Early detection can improve safety response times and inform mitigation decisions. Our intention was to evaluate whether inexpensive ground-based vibration sensors can automatically detect avalanches and distinguish them from other seismic sources in this corridor.

The Viotel accelerometer occupies a useful position in the market: it provides ultra-low-noise performance comparable to instruments costing 10x more, at a price point far below seismological-grade stations. At the same time, it offers significantly better sensitivity than commodity MEMS sensors (which cost 10x less but have noise floors too high for this application).

Objectives

1. Primary: Determine whether avalanches produce a detectable and classifiable seismic signature
2. Primary: Develop an automated classification algorithm to distinguish avalanches from other sources
3. Secondary: Classify all detected seismic events (trains, earthquakes, artefacts)
4. Secondary: Evaluate sensor performance, detection range, and operational reliability

Approach

- Deploy three Viotel accelerometers along the corridor
- Collect continuous 62.5 Hz 3-axis acceleration data via LTE-M cellular telemetry
- Develop event detection and classification algorithms
- Validate against train schedules, USGS earthquake catalog, and avalanche observations

Sensor Deployment

Sensor Specifications

Parameter	Value
Sensor	Viotel ultra-low-noise 3-axis MEMS accelerometer
Sampling rate	62.5 Hz
Resolution	20-bit (+/-2g range)
Noise density	~25 ug/sqrt(Hz)
RMS noise floor	~0.094 in/s ² (3-axis vector)
Telemetry	LTE-M cellular (continuous upload)
Power	Battery (supplied by Matt McKee)
Timing	GPS PPS disciplined

Station Locations

Device	Latitude	Longitude	Distance to Track	Elevation Relative to Track	Status
viot01300	60.9167 N	149.1040 W	~100 ft	At grade	Buried by avalanche 15 Jan 2026
viot01301	60.9149 N	149.0997 W	~100 ft	At grade	Active (full period)
viot01318	60.9009 N	149.0731 W	~90 ft	~45 deg slope, above track	Active (full period)

The three stations are arranged along the corridor:

- viot01300 and viot01301 are 1,000 ft apart (same reference camera at Kern)
- viot01318 is 1.3 miles further along the corridor (camera at Kern, with +3 min time offset for train travel time)
- All sensors are within 100 ft of the Alaska Railroad track



Figure 1 — Three-station deployment along the Turnagain Arm corridor.

Data Collection Summary

Device	Data Period (AKST)	Days	Events Detected	Notes
viot01300	19 Dec 2025 - 15 Jan 2026	28	43	Lost to avalanche
viot01301	19 Dec 2025 - 12 May 2026	145	261	Primary station
viot01318	19 Dec 2025 - 12 May 2026	145	96	Lower train event rate (see Results)

Total: 400 seismic events detected across all three stations.

The Avalanche Event

Confirmed Detection

On 15 January 2026 at 20:28 AKST, a large avalanche was recorded on station viot01301. This event was independently confirmed by field observations and camera imagery. The avalanche flowed to within approximately 30 ft of the sensor.

We suspect a separate, earlier avalanche that same evening buried station viot01300 (1,000 ft away). The last data successfully uploaded from viot01300 covers up to 17:50 AKST on 15 January. We estimate the burial occurred within minutes of this last upload, as the device's internal buffer would normally continue uploading for only a short period after data acquisition. Camera observations confirmed the burial but the exact time is uncertain.

Examination of viot01301 data around 17:50 AKST shows no elevated signal — the background amplitude remained at the noise floor (maximum 4.1 mm/s² vs. the 31 mm/s² peak of the later avalanche). This confirms that the earlier avalanche that buried viot01300 was either smaller, on a different path, or both — and was not detectable at viot01301's location 1,000 ft away.

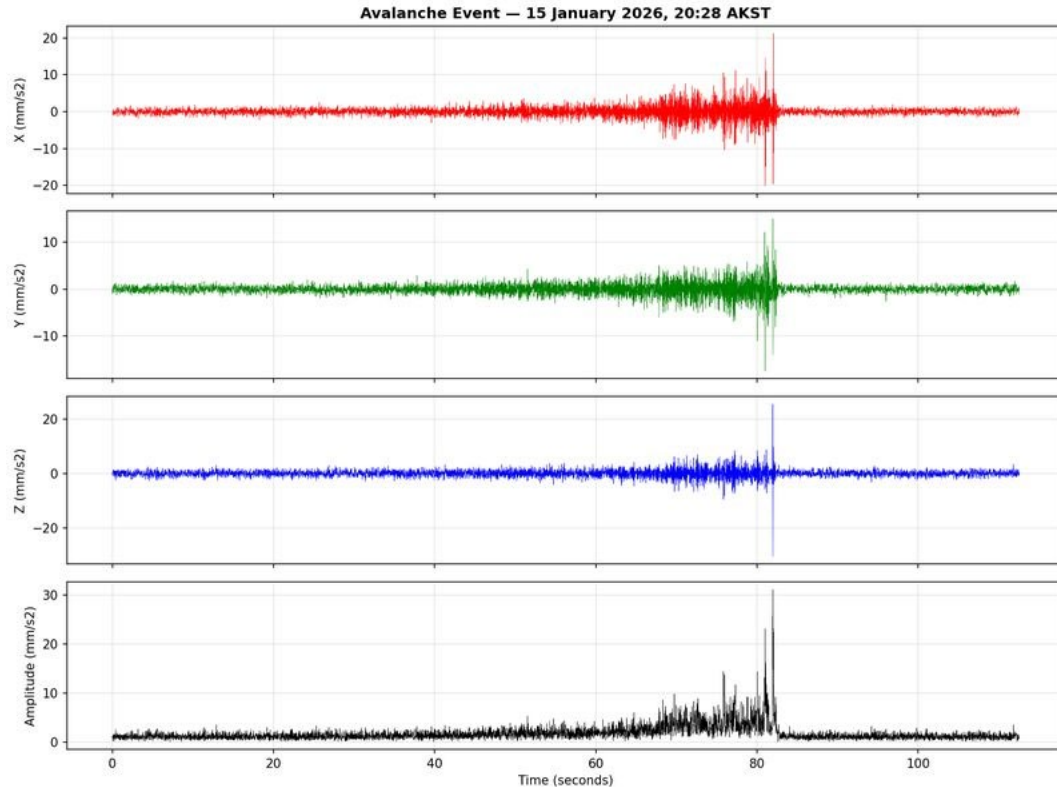


Figure 2 — Three-component accelerogram of the confirmed (second) avalanche event (15 January 2026, AKST). Note the gradual onset, extended duration, and brief high-amplitude burst.

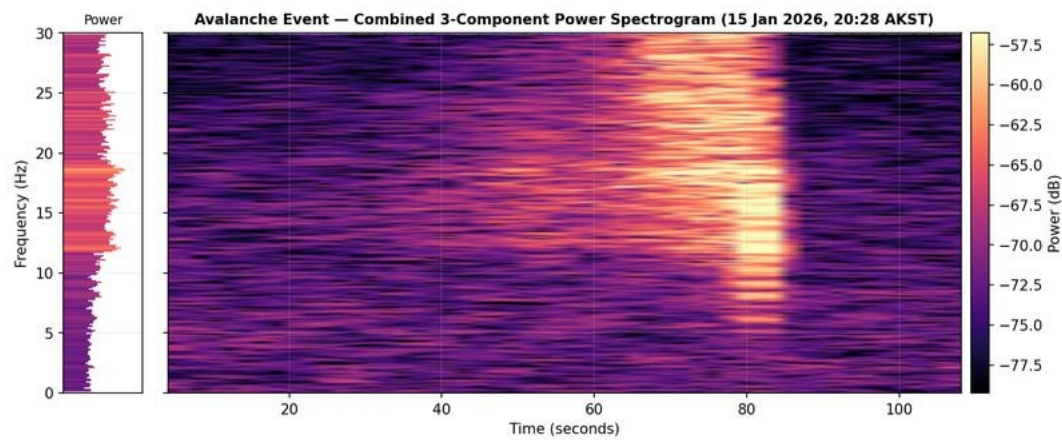


Figure 3 — Spectrogram of the avalanche event. The dominant energy is concentrated around 18 Hz, though broadband energy is visible during the peak amplitude burst.

Avalanche Signature

The confirmed avalanche has a distinctive seismic signature:

Feature	Avalanche	Typical Train	Typical Earthquake
Duration	181 s	141 +/- 86 s	22 +/- 11 s
Peak amplitude	1.22 in/s ²	1.51 +/- 0.44 in/s ²	0.72 +/- 0.28 in/s ²
RMS amplitude	0.079 in/s ²	0.35 +/- 0.11 in/s ²	0.15 +/- 0.04 in/s ²
Crest factor	15.9	4.4 +/- 1.2	4.9 +/- 1.1
Spectral centroid	18.8 Hz	9.4 +/- 1.7 Hz	6.9 +/- 1.2 Hz
LF/HF 3D-amp energy ratio	2.36	1.33 +/- 0.47	2.13 +/- 0.52
High sample fraction	0.04%	2-3%	1-2%

High sample fraction: the percentage of samples exceeding 50% of peak amplitude. A low value means energy is concentrated in a very brief burst rather than sustained throughout the event.

LF/HF 3D-amp energy ratio: the 3-component signal is processed to obtain rectified amplitude vs time, and then analysed to extract spectral ratio.

Five features distinguish the avalanche from all other event types:

1. Very high crest factor (15.9): The avalanche energy arrives in a short burst within a long event — a brief intense peak on a low-amplitude background.
2. High spectral centroid (18.8 Hz): Dominated by high frequencies, consistent with hard impacts - possibly rocks-on-rocks, moved by snow. It would be good if we could discard this parameter, and drop the sampling rate to improve power consumption.
3. LF/HF 3D-amp energy ratio (2.36): spectral ratio of the rectified 3D amplitude.
4. Gradual onset: Unlike the impulsive P-wave arrival of earthquakes.
5. Low sustained energy: Despite high peak amplitude, the RMS is very low. Energy is concentrated in a ~30 s burst within a 3-minute event.

Distinction from Other Sources

- vs. Trains: Trains sustain high amplitude for minutes (high RMS). The avalanche has a brief peak on a quiet background.
- vs. Earthquakes: Earthquakes have impulsive onsets (P-wave). The avalanche has a gradual, emergent onset.
- vs. Spikes: Spikes are extremely short (< 5 s) with only 1-3 high samples. The avalanche is extended (181 s).

Classification Algorithm

Architecture

A hybrid three-stage classifier was developed:

Stage 1: SPIKE DETECTION (rule-based)

If ≤ 3 samples above 50% of peak $\rightarrow$ SPIKE

Stage 2: ML CLASSIFICATION (Random Forest)

Trained on labeled train/earthquake events

100 trees, 20 features, 5-fold cross-validation

Stage 3: AVALANCHE DETECTION (rule-based)

Crest factor ≥ 8.0

LF/HF ratio ≥ 2.0

Duration ≥ 30 s

High sample fraction $\leq 1\%$

Spectral centroid ≤ 7.0 Hz

ALL criteria must be met $\rightarrow$ AVALANCHE

Classification Decision Flow

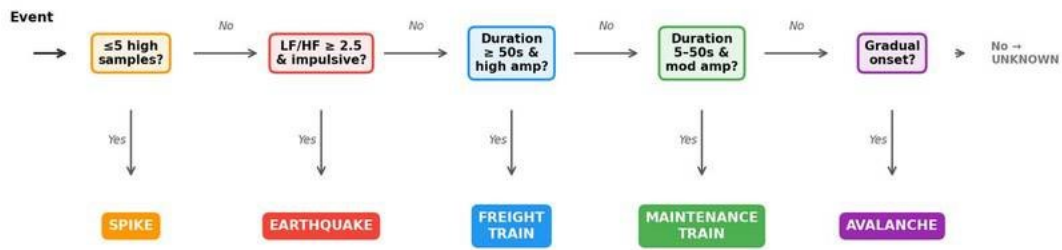


Figure 4 — Classification algorithm decision flow.

Why a Hybrid Approach?

Machine learning works well for trains and earthquakes where we have dozens of labeled examples. Rule-based detection is necessary for avalanches because we have only one confirmed example — insufficient for ML training. The avalanche rules are deliberately conservative: all 5 criteria must be satisfied to minimise false alarms.

Training Data

Within the camera observation period (21 January - 11 March 2026 AKST), 82 events at viot01301 were labeled:

Event Type	Count	Label Source
Freight Train	40	Camera schedule cross-reference
Track Maintenance	8	Camera schedule cross-reference
Hyrail Truck	3	Camera schedule cross-reference
Earthquake	9	USGS catalog + travel-time matching
Spike (artefact)	16	Waveform inspection
Unknown	8	No matching external data

Plus 1 confirmed avalanche (outside camera observation period). Of the 9 earthquakes, 7 occurred during the camera observation period and 2 were identified from USGS catalog matching in the preceding weeks.

Earthquake Matching

Earthquakes are identified using physics-based seismic travel-time windows:

Matching window: $[T_0 + D/v_P - 10s, T_0 + D/v_L + 10s]$

where T_0 is the earthquake origin time (USGS catalog), D is the 3D source-to-station distance, $v_P = 4.0$ mi/s (P-wave velocity) and $v_L = 1.5$ mi/s (Love-wave velocity). This is far more selective than a fixed time window and eliminates false matches from coincidental timing.

Results

Classification Accuracy (viot01301)

5-fold stratified cross-validation on 76 certain events. The table below reports four standard metrics. Precision is the fraction of events predicted as a given class that truly belong to that class (how trustworthy a positive prediction is). Recall is the fraction of true events that the algorithm correctly identifies (how many real events it catches). F1-Score is the harmonic mean of precision and recall. Support is the number of true examples of each class.

Class	Precision	Recall	F1-Score	Support
Earthquake	86%	67%	75%	9
Spike	94%	100%	97%	16
Train	96%	98%	97%	51
Overall	94%	95%	94%	76

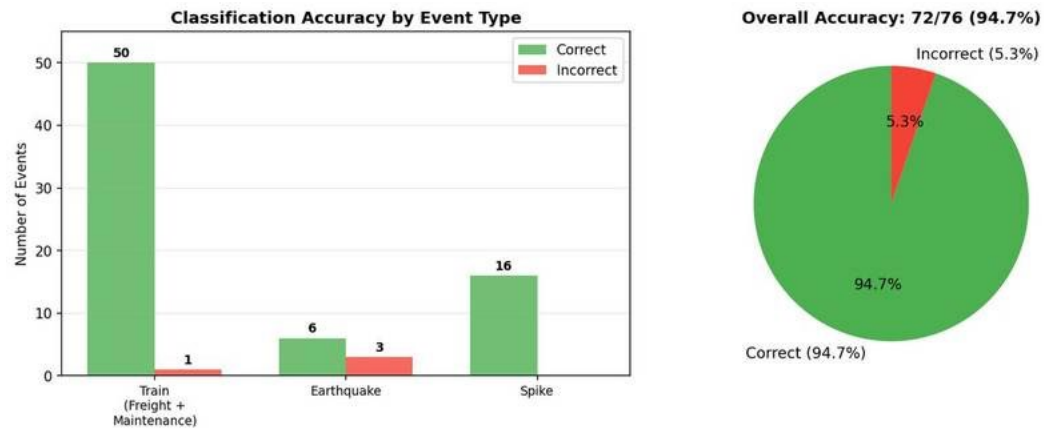


Figure 5 — Cross-validation accuracy by event class.

Confusion matrix:

	Pred: Earthquake	Pred: Spike	Pred: Train
True: Earthquake	6	1	2
True: Spike	0	16	0
True: Train	1	0	50

The confirmed avalanche correctly satisfies all rule-based avalanche criteria.

Avalanche Detection Performance

The avalanche detection rules were applied to all 261 events at viot01301:

- True positive: 1 (the confirmed avalanche on 15 January 2026)
- False positives: 0

This cannot be considered a robust validation with only one true event. The conservative thresholds (derived from a single example) may be too restrictive or too permissive — we cannot know without additional confirmed avalanches.

Multi-Station Results

Metric	viot01301	viot01318	viot01300
Data period	145 days	145 days	28 days
Events detected	261	96	43
ML accuracy (CV)	94.7%	65.3%	N/A
Earthquakes detected	7 (M3.1-M4.6)	22 (M2.3-M4.6)	1 (M2.1)
Train peak amplitude	1.51 +/- 0.44 in/s ²	0.63 +/- 0.16 in/s ²	~1.77 in/s ²
Avalanche detected	Yes (1)	No	Buried by avalanche

viot01318 detects fewer train events despite being a similar horizontal distance from the track. We attribute this to the sensor's installation on a steep (~45 degree) slope above the track. Research on railway ground-borne vibration has demonstrated that elevation differences between source and receiver significantly affect vibration propagation: when the receiver is elevated above the track, the propagation path is longer and passes through additional material, leading to greater attenuation (Kouroussis et al., 2016; Bian et al., 2021). The ~60% reduction in train amplitude at viot01318 is consistent with this effect.

Earthquake detection is excellent at both active stations — 22 earthquakes detected at viot01318 including events as small as M2.3 at 9 miles. Earthquake signals propagate as body waves from depth and are less affected by surface topography.

The lower ML accuracy at viot01318 (65%) is due to weak train signals being confused with background. The amplitude thresholds need per-sensor calibration.

Extended Monitoring (March-May 2026)

After the camera observation period ended (11 March 2026 AKST), monitoring continued through 12 May 2026:

- viot01301: Continued detecting events (261 total over full period)
- viot01318: Only 2 events detected from 22 March - 12 May 2026 (one 62 s event on 20 April, one 3 s spike on 29 April)
- No additional avalanches were detected at either station

The very low event rate at viot01318 in spring (2 events in 52 days vs. 94 in the first 93 days) possibly reflects reduced train traffic and the end of avalanche season.

Event Type Examples

Freight Train

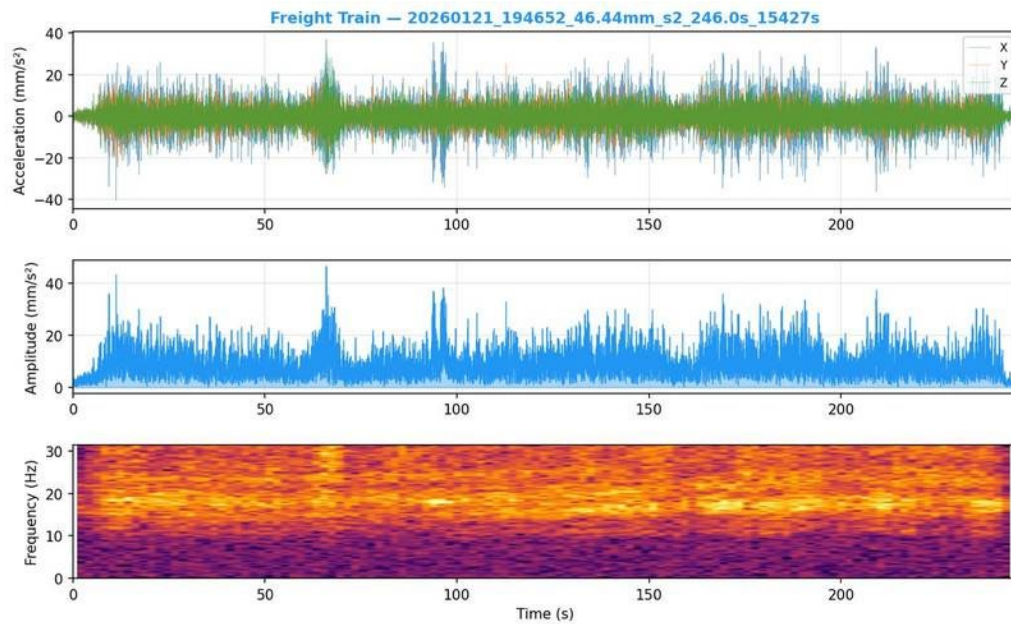


Figure 6 — Typical freight train signal: sustained high amplitude for 2-4 minutes, broadband energy.

Track Maintenance Equipment

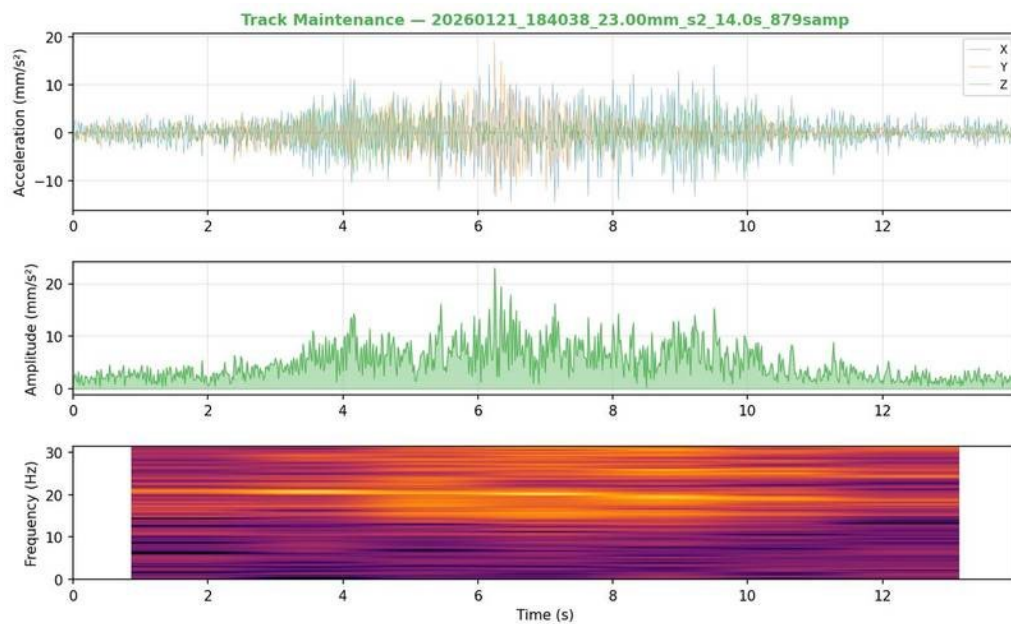


Figure 7 — Track maintenance equipment: shorter duration (5-50 s), moderate amplitude, similar spectral content to freight trains.

Earthquake

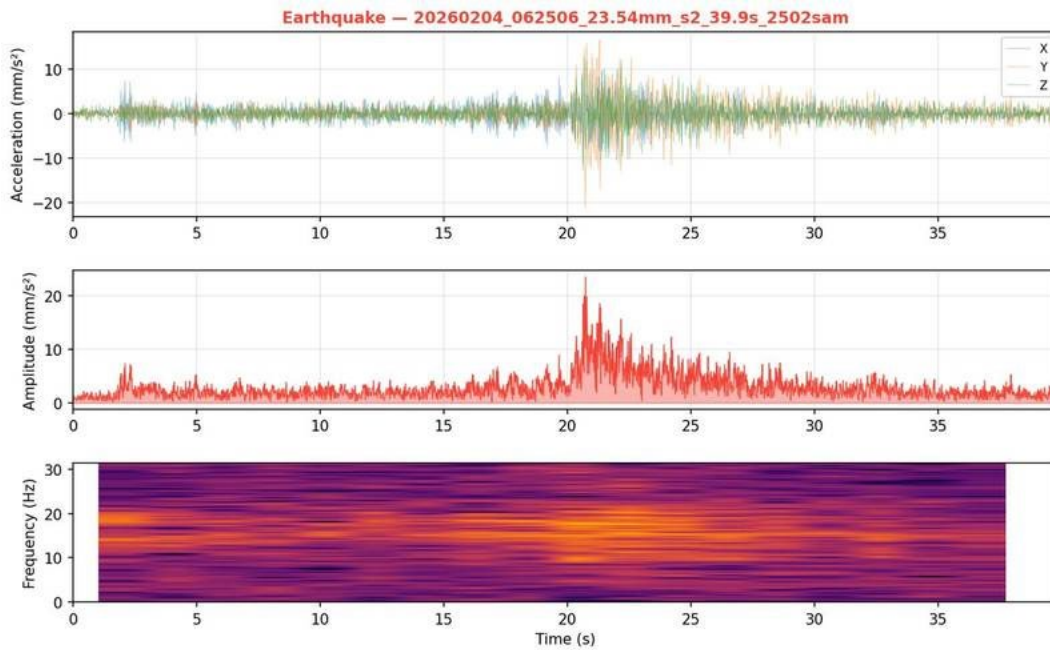


Figure 8 — Earthquake signal (M4.6, 57 miles): impulsive onset, short duration, low-frequency content.

Spike (Artefact)

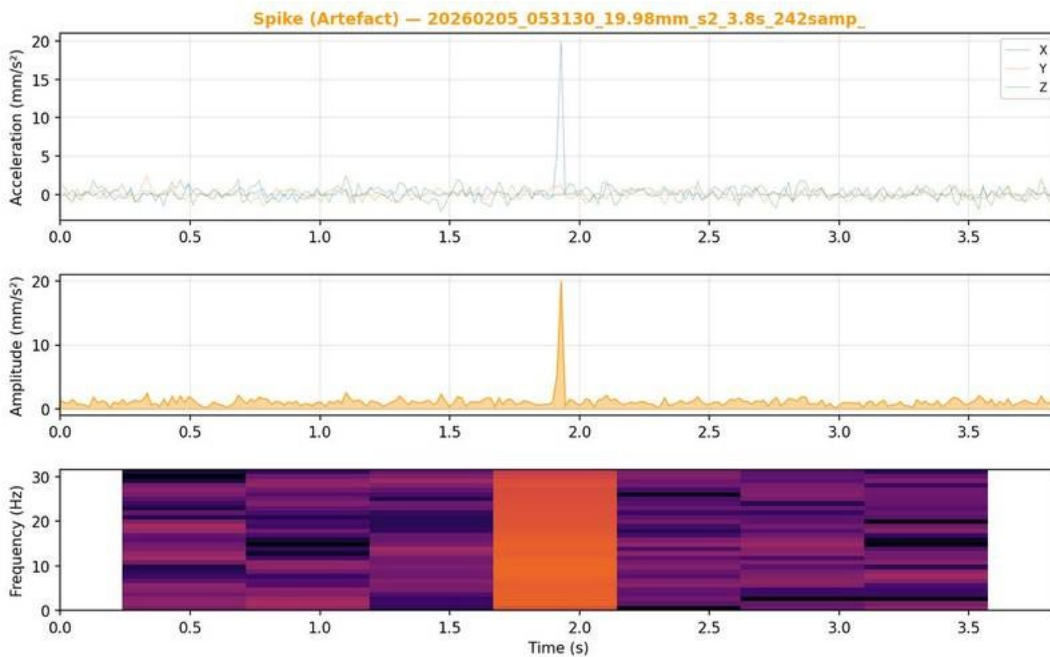


Figure 9 — Sensor artefact: extremely brief (1-3 samples), non-physical signal.

Feature Comparison

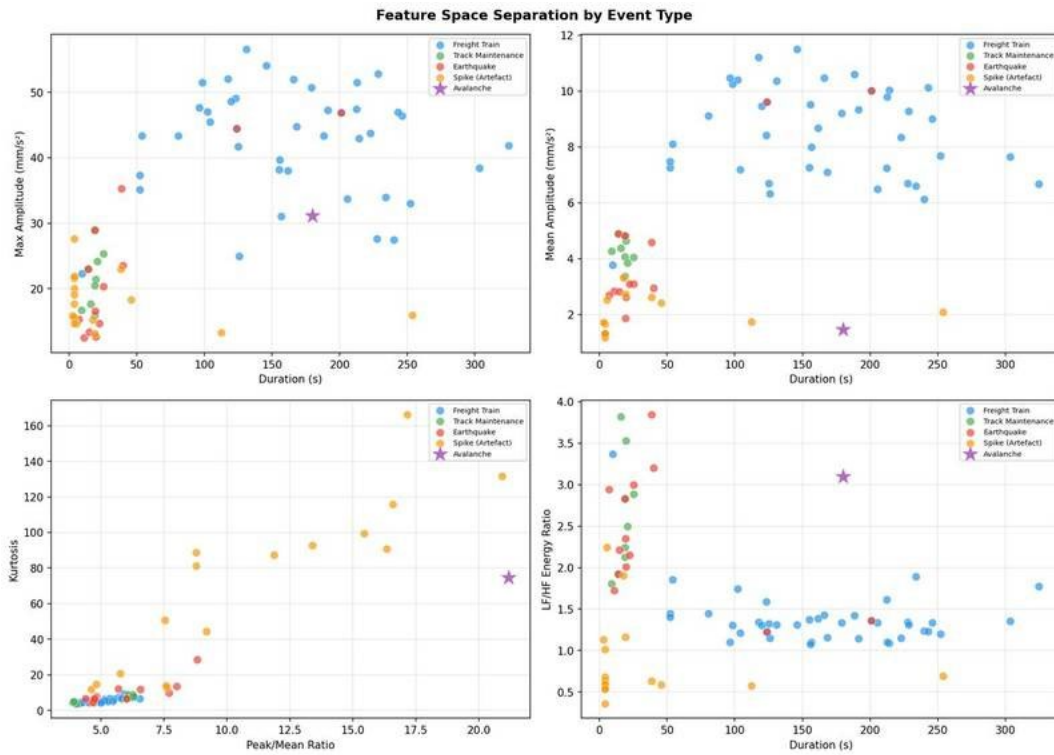


Figure 10 — Feature space comparison across event types. The avalanche (large red star) occupies a distinct region characterised by high crest factor and low spectral centroid.

Operational Performance

Sensor Reliability

Device	Uptime	Data Gaps	Notes
viot01300	100% (until burial)	None	Lost to avalanche 15 Jan 2026 AKST
viot01301	>99%	Minor (<1 hr total)	Continuous operation 145 days
viot01318	>99%	Minor (<1 hr total)	Continuous operation 145 days

The sensors demonstrated excellent operational reliability over the full winter season, with no significant data gaps or failures (other than the physical destruction of viot01300 by the avalanche itself). No maintenance visits were required.

Detection Capability

Source Type	Detection Range	Minimum Detected
Freight train	~100 ft (strong)	All trains within 100 ft at grade
Earthquake	60+ miles	M2.3 at 9 miles, M3.1 at 62 miles
Avalanche	Confirmed at ~30 ft; not detected at 1.3 miles	1 event

The avalanche at 20:28 AKST flowed to within approximately 30 ft of viot01301, which recorded a clear signal (13:1 SNR). Station viot01318, located 1.3 miles away, did not detect this event. The earlier avalanche that buried viot01300 was not detected on viot01301 (1,000 ft away). These observations establish that the detection range is limited — confirmed at 30 ft, but not reliable at 1,000 ft for a smaller event or 1.3 miles for a larger one. Further work with additional avalanche events is needed to characterise the detection radius.

Amplitude vs. Time

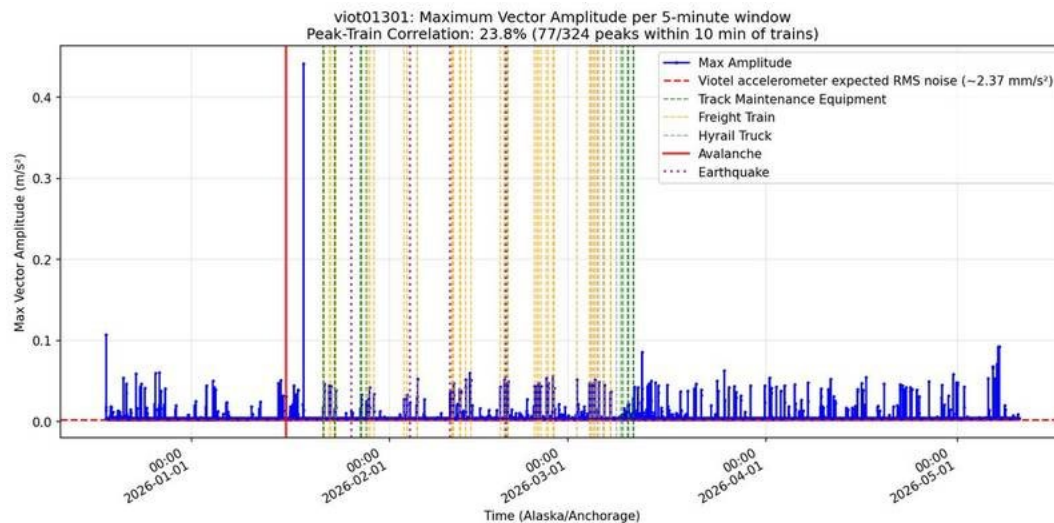


Figure 11 — Maximum vector amplitude per 5-minute window at viot01301 over the full monitoring period. Orange lines indicate confirmed train passages; red line marks the avalanche.

Discussion

Can We Detect Avalanches?

Yes. The confirmed avalanche produced a clear signal (1.22 in/s² peak) well above the sensor noise floor (0.094 in/s²) — a signal-to-noise ratio of 13:1. The signal has distinctive characteristics that separate it from all other sources recorded during the deployment.

Can We Classify Avalanches Automatically?

Provisionally yes, but not yet validated. The rule-based avalanche criteria correctly identify the one confirmed event with zero false positives over 145 days. However, the thresholds are derived from a single example. We cannot calculate meaningful detection probability from $n=1$, and we cannot know whether the thresholds will generalise to avalanches of different sizes, distances, or snow conditions.

What Would a Second Year Provide?

A second monitoring season would:

1. Validate the avalanche detection rules against new confirmed events
2. Refine thresholds if the current rules are too restrictive or too permissive
3. Enable ML-based avalanche classification if 5+ examples are collected
4. Characterise avalanche variability — do all avalanches produce a similar signature, or does it vary with size, distance and snow type?
5. Test operational deployment — can the system provide timely alerts?

Limitations

1. Single avalanche example. All avalanche-specific conclusions are based on $n=1$.
2. No negative avalanche confirmation. We assume periods without detected avalanches truly had none, but this is not independently verified for the full period.
3. Sensor burial. viot01300 was lost after 28 days, reducing the multi-station analysis period.
4. Train observation gap. Camera-based train observations ended 11 March 2026 AKST. Events after this date cannot be validated against train schedules.
5. Earthquake/train boundary. Distant, weak earthquakes (M3.1-3.6 at 56-62 miles) produce signals similar to short train events, causing 2/9 earthquake misclassifications.

Conclusions

These field trials have demonstrated that:

1. Inexpensive ultra-low-noise MEMS accelerometers can detect avalanches in a transportation corridor with a signal-to-noise ratio of 13:1.
2. The avalanche signature is distinctive — low spectral centroid (< 7 Hz), very high crest factor (> 8), gradual onset, and low sustained energy relative to peak amplitude.
3. Automated classification is feasible. The hybrid ML + rule-based approach achieves 94.7% accuracy on non-avalanche events and correctly identifies the confirmed avalanche.
4. The algorithm cannot yet be validated with only one confirmed event. Statistical confidence requires multiple independent avalanche observations.
5. The sensors are operationally reliable — $>99\%$ uptime over a full Alaska winter with no maintenance visits required.
6. Earthquake detection is a valuable secondary capability — the sensors detect regional earthquakes as small as M2.3, providing useful seismic monitoring data.

Recommendations

Immediate

- Continue monitoring through the 2026-2027 winter season to collect additional avalanche examples
- Replace viot01300 (buried) to restore three-station geometry

For Year 2 (if approved)

- Validate avalanche detection rules against new confirmed events
- Collect 5+ avalanche examples to enable ML-based classification
- Integrate real-time USGS earthquake feed for operational earthquake filtering
- Evaluate alert latency — how quickly can an avalanche be detected and classified after onset?
- Test multi-station correlation — can two stations confirm an avalanche and reject false alarms?

Long-term

- On-device classification — the Random Forest and feature extraction are lightweight enough for edge deployment
- Real-time alerting — integrate with DOT/railroad notification systems
- Network expansion — additional sensors along the corridor to characterise avalanche paths and sizes

Appendix A: Detected Earthquakes (viot01318)

Date (AKST)	Magnitude	Distance (miles)	Location
22 Dec 2025	M3.2	60	Point Possession
25 Dec 2025	M2.9	45	Point Possession
11 Jan 2026	M3.2	58	Meadow Lakes
18 Jan 2026	M2.5	50	Big Lake
19 Jan 2026	M3.0	62	Fishhook
25 Jan 2026	M2.3	9	Girdwood
26 Jan 2026	M3.6	48	Big Lake
30 Jan 2026	M3.2	22	Elmendorf AFB
31 Jan 2026	M3.2	52	Big Lake
5 Feb 2026	M3.1	51	Houston
9 Feb 2026	M2.4	12	Girdwood
10 Feb 2026	M4.6	57	Meadow Lakes
12 Feb 2026	M3.6	47	Sterling
12 Feb 2026	M3.3	48	Point MacKenzie
13 Feb 2026	M3.2	58	Meadow Lakes
13 Feb 2026	M3.7	57	Meadow Lakes
20 Feb 2026	M3.6	58	Point Possession
26 Feb 2026	M3.1	44	Point Possession
9 Mar 2026	M3.6	62	Sutton-Alpine
11 Mar 2026	M3.7	52	Meadow Lakes
17 Mar 2026	M3.1	34	Whittier
18 Mar 2026	M3.4	54	Meadow Lakes

Appendix B: Algorithm Feature Set

The Random Forest classifier uses 20 features extracted from each event waveform:

Category	Features
Amplitude	Peak, RMS, mean amplitude
Shape	Kurtosis, skewness, crest factor
Temporal	Duration, rise time, rise fraction, energy entropy
Spectral	Centroid, bandwidth, dominant frequency, LF/HF ratio, mid-band ratio
Envelope	High sample count, high sample fraction, decay ratio, first-half energy ratio

Top 5 feature importances (Random Forest):

1. RMS amplitude (0.169)
2. Mid-band energy ratio (0.150)
3. Number of high samples (0.140)
4. Kurtosis (0.097)
5. Peak amplitude (0.073)

Appendix C: Data Availability

All raw accelerometer data, processed waveforms, and classification results are archived in the project repository:

- `viot01300/raw/` — Raw accelerometer data (19 Dec 2025 - 15 Jan 2026 AKST)
- `viot01301/raw/` — Raw accelerometer data (19 Dec 2025 - 12 May 2026 AKST)
- `viot01318/raw/` — Raw accelerometer data (19 Dec 2025 - 12 May 2026 AKST)
- `trimmed\_waveforms/` — 261 extracted events (viot01301)
- `trimmed\_waveforms\_viot01318/` — 94 extracted events (viot01318)
- `trimmed\_waveforms\_viot01300/` — 43 extracted events (viot01300)
- `classification\_results\_viot01318.csv` — Classification output for viot01318
- `classification\_results\_viot01300.csv` — Classification output for viot01300
- `Algorithm-and-Reporting/classification\_results.csv` — Classification output for viot01301
- `earthquakes.csv` — USGS earthquake catalog for the region
- `train-times.csv` — Camera-observed train schedule (Kern)
- `train-times-viot01318.csv` — Train schedule adjusted for viot01318 (+3 min offset)

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