Assessing Driving Risk using Telematics Data a Wavelet Transform Approach

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June 29, 2026

Outline

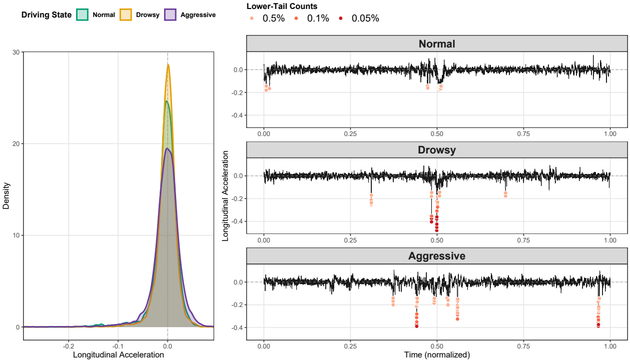
Background and Motivation

- This project was stemmed from multi-year collaboration between our group and Geotab Inc, a global leader in connected transportation solutions and telematics data collection and management.
- We have been involved in some of their projects on real-world telematics problems.
    - *Assessing driving risk with enriched telematics signals*
    - *Collision detection using high-rate telematics data*
    - *Identifying hazardous driving areas and accident propensity*
    - *Telematics-driven vehicle-driver predictive safety benchmarking for fleet operations*
    - *Weight detection for heavy-duty vehicles*
- All of these projects are centered at evaluation and classification of driving risk at both the trip level and the driver level, and in a data-driven way.

From Insurance Perspective

- From an actuarial viewpoint, the core objective is not only prediction, but also **risk differentiation, ranking and quantification - pricing**.
- Although telematics data, as time series data, provide very rich behavioral information of drivers at the trip level, most research use drivers' attributes (as covariates) and summary statistics of trips, and employs a regression modelling framework.
- Such an approach clearly has issues:
  - it does not fully utilize the rich behaviour information embedded in telematics data.
  - Summary statistics are sensitive to how they are calculated and often problematic, especially when the trip length and the scale of event count varies from trip to trip and from driver to driver.
  - a small change can have a significant effect on a regression model.
  - As a result, accurate quantifying and ranking the risk of trips and drivers across the board can be challenging.

How Do Driving Behaviours Look like?



- In order to quantify driving risk one must take two factors into account: how often risky behaviour occurs and how severe it is.

Our Approach

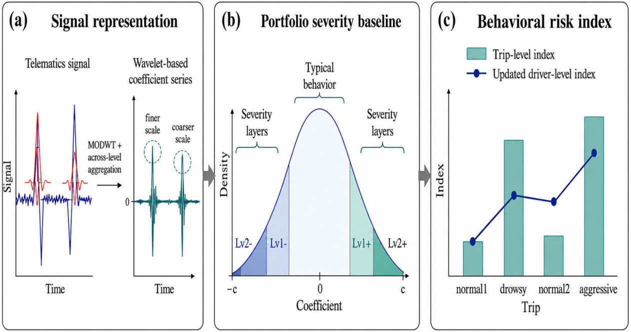


Figure: Panel (a): how telematics signals of each trip are transformed into a wavelet-based representation. Panel (b): the fitted severity model where the Gaussian component describes typical patterns, while Uniform layers represent increasingly extreme patterns. Panel (c): an example of trip-level index for each behavioral state and sequentially updated driver-level index.

MODWT for Telematics Data

- Telematics signals are time series data with rich local temporal structure.
- Risk-relevant behaviours such as:
  - harsh braking,
  - harsh/sudden acceleration,
  - short bursts of oscillation,
  - sustained abnormal manoeuvres

  are often localized in time and may occur at different durations.
- Wavelets are attractive because they naturally capture:
  - short-lived local deviations at fine scales.
  - longer sustained patterns at coarser scales.
- This makes wavelet representations especially suitable for extracting risk-relevant transient driving patterns.

Data Representation

- For trip j, let the longitudinal acceleration signals be

$$X_j = (X_{j,t})_{t=0}^{T_j-1}.$$

- For level l, MODWT produces wavelet coefficients

$$\widetilde{W}_{j,l,t} = \sum_{k=0}^{K_l-1} \widetilde{h}_{l,k} X_{j,(t-k) \bmod T_j}, \qquad t = 0, \ldots, T_j - 1,$$

  where filters $\widetilde{h}_{l,k}$ at level l are generated from the *Daubechies D4* wavelet filter through dyadic dilation.

- Interpretation:
  - small $l \Rightarrow$ short-duration local changes,
  - large $l \Rightarrow$ smoother, longer-duration changes.
  - in general, 6 levels is sufficient to capture driving behaviour changes.

Across-Level Aggregation

- A risky manoeuvre need not appear at only one level (or scale).
- Hence, we aggregate the MODWT coefficients across selected levels:

$$C_{j,t} = \max_{l \in \mathcal{L}} \left| \widetilde{W}_{j,l,t} \right|, \qquad t = 0, \cdots, T_j - 1,$$

  where $\mathcal{L} = \{1, \ldots, L\}$.

- Interpretation:
  - at each time point, $C_{j,t}$ records the largest multi-scale deviation,
  - so short, medium, and long abnormal patterns all compete to be represented.
- This yields a single trip-level time series

$$C_j = (C_{j,0}, \cdots, C_{j,T_j-1}).$$

Modelling Severity of Acceleration/Braking

- All the trip level time series data are sampled by a hierarchical sampling with thinning within each of the trips.
- The retained time series data are then pooled to form a sample that serves as an input to the portfolio-level severity model.
- The central idea:
  - typical behaviour should define a stable baseline,
  - abnormal behaviour should be absorbed by explicit tail components.
- A Gaussian–Uniform mixture is used and fitted with a specific EM algorithm:
  - Gaussian component(s): normal/typical driving behaviour,
  - multiple Uniform components on the left and right tails:
    - left tail = harsh braking/deceleration;
    - right tail = harsh acceleration.
- Each Uniform component defines a severity layer.
- Layers farther from the center correspond to:
  - rarer behaviour,
  - more extreme behaviour.

Why to Use the Gaussian–Uniform Mixture Model?

- Longitudinal acceleration often has an approximately Gaussian central behaviour.
- But a pure Gaussian fit is problematic for telematics risk scoring:
  - tail extremes inflate the fitted variance,
  - the “normal” baseline becomes unstable,
  - abnormality becomes sensitive to portfolio composition in terms of drivers’ style.
- By explicitly allocating tail observations to Uniform components:
  - the Gaussian core remains stable and interpretable,
  - the tail is structured into ordered rarity layers,
  - severity is measured at a common portfolio-level scale.
  - such an approach allows for meaningful comparison across trips and across drivers, even when trip lengths and driving styles differ.

Modeling Signal Count within Each Layer

- Once the severity layers are estimated, each $C_{j,t}$ is assigned to: a left-tail layer, a right-tail layer, or the Gaussian core.
- For trip j, we count how often the signal enters each layer:

  Multi-Layer Tail Counts (MLTC)

- Thus, a trip is summarized not only by: how many abnormal patterns occur, but also by how deep into the tails.
- Layer-wise counts are modeled using a Poisson–Gamma model.
- The resulting posterior weighted intensity with weights proportional to severity, yields:
  - an exposure-normalized trip-level (behaviour) risk index, and
  - allows sequential Bayesian updating at the driver level.

A Controlled Study: Data Description

- We apply the proposed framework to a labelled dataset 'UAH-DriveSet' from

  Romera, E., Bergasa, L. M. and Arroyo, R. (2016) "Need data for driver behaviour analysis? presenting the public UAH-driveset." In *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, pp. 387–392. IEEE.

  to validate its effectiveness in anomaly detection.

- *Five* different drivers and vehicles are asked to perform three distinct driving behaviour (normal, aggressive and drowsy) on two different roads (a motorway and a secondary road).

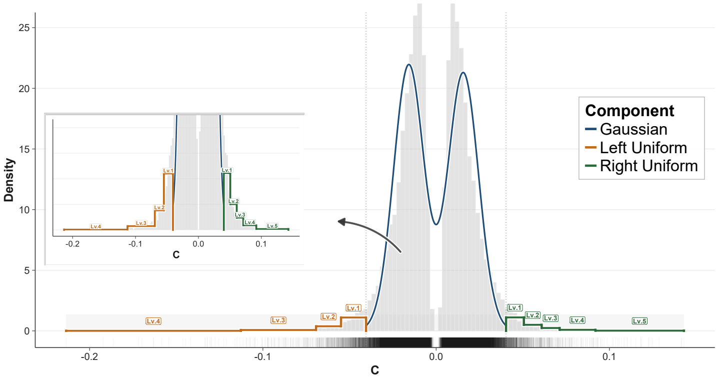
- Telematics recording starts when the vehicle enters the specific road and ends when it exits, hence speed is always non-zero.

- Note that none of the drivers has been involved in accidents, which is not as useful from an actuarial perspective.

- We are currently working closely with Geotab to acquire their collision data for this project.

Fitting Severity Model

- We fit the severity and frequency components using all 40 trips pooled across secondary and motorway roads.
- This creates a common portfolio baseline and common severity scale.



Frequency–Severity Representation for Trip j

For trip j, let

$$C_j = (C_{j,0}, \cdots, C_{j,T_j-1})$$

be the aggregated MODWT coefficient series.

Using the fitted portfolio-level Gaussian–Uniform mixture model, each coefficient is assigned into one of the ordered severity layers:

$$\Theta_1, \Theta_2, \ldots, \Theta_M,$$

where deeper tail layers correspond to more extreme driving behaviour.

For layer m, define the layer-wise count

$$N_{j,m} = \sum_{t=0}^{T_j-1} \mathbf{1}(C_{j,t} \in \Theta_m),$$

which represents how often trip j exhibits severity level m behaviour.

Behaviour Risk Index

For each severity layer m, we model

$$N_{j,m} \mid \lambda_{j,m} \sim \text{Poisson}(E_j \lambda_{j,m}),$$

where:

- E_j = exposure (trip length),
- $\lambda_{j,m}$ = latent risk intensity for layer m.

Using the conjugate prior

$$\lambda_{j,m} \sim \text{Gamma}(\alpha_m, \beta_m),$$

the posterior mean becomes

$$\widehat{\lambda}_{j,m} = \frac{\alpha_m + N_{j,m}}{\beta_m + E_j}.$$

The proposed frequency–severity trip-level risk index is

$$R_j = \sum_{m=1}^{M} w_m \, \widehat{\lambda}_{j,m},$$

where:

- w_m are severity weights,
- larger weights are assigned to deeper tail layers.

Behaviour Risk Index

Driver	Label	Exposure (E_i)	Behavioral Risk Index ($\times 10^{-4}$) Trip	Driver
D1	normal1	411	3.47	3.47
	aggressive	354	**15.64**	9.49
	normal2	435	5.42	7.75
	drowsy	335	**14.89**	9.75
D2	normal1	434	4.32	4.32
	aggressive	411	**34.84**	20.83
	normal2	458	4.31	15.01
	drowsy	434	**20.52**	17.52
D3	normal1	466	3.09	3.09
	aggressive	452	**10.44**	6.21
	normal2	446	4.28	4.99
	drowsy	442	**7.98**	5.51
D4	normal1	486	3.14	3.14
	aggressive	441	**11.09**	6.46
	normal2	460	3.69	4.92
	drowsy	458	**6.41**	4.95
D5	normal1	467	3.97	3.97
	aggressive	282	**41.59**	19.93
	normal2	462	6.27	14.72
	drowsy	467	**6.43**	12.27
D6	normal	519	6.75	6.75
	drowsy	480	**11.20**	8.99

Behaviour Risk Index

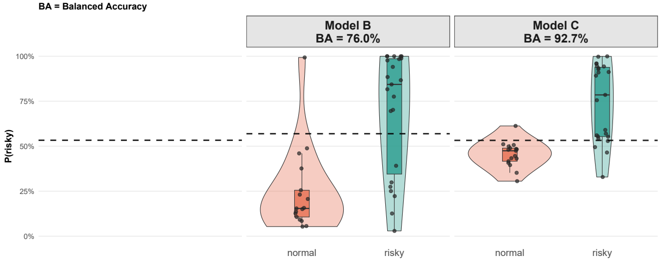
- The proposed index provides a coherent cross-trip ranking because all trips are measured against the same portfolio-level severity scale.
- In the controlled study:
  - risky trips (aggressive/drowsy) generally have higher trip-level risk than normal trips,
  - but the reason can differ:
    - aggressive: often more frequent abnormal patterns across many layers,
    - drowsy: sometimes low frequency with deeper tail penetration.
- Interpretation:
  - normal trips tend to have smaller MLTC totals and shallower layers,
  - aggressive trips tend to spread mass across multiple layers,
  - drowsy trips can have fewer total counts but reach deeper layers.

Binary Classification Validation

- We validate the proposed framework by a binary task:

  normal vs. risky (aggressive or drowsy)

- Two models are compared:
  1. Model B: layer-wise counts only,
  2. Model C: proposed joint frequency–severity risk index.



Contributions of this Approach

- This approach is fully signal-driven:
  - no claims labels,
  - no demographic or vehicle covariates,
  - no manually defined harsh-event thresholds.
- It contributes three things simultaneously:
  1. a time-series representation that preserves local driving dynamics,
  2. a formal notion of severity anchored to portfolio-level rarity,
  3. a dynamic trip-to-driver updating mechanism.
- From an actuarial viewpoint, this is attractive because it supports:
  - trip-level ordering,
  - driver-level monitoring,
  - dynamic UBI-style pricing,
  - reduced dependence on potentially biased traditional covariates.

Ongoing Project

- Currently we use only longitudinal acceleration.
- The next extension is multivariate:
  - longitudinal acceleration,
  - lateral acceleration,
  - speed as a contextual modifier.
- Why multivariate?
  - driving manoeuvres such as drifting, harsh cornering, lane-changing, or tailgating are better characterized jointly.
- Proposed direction:
  - perform level-wise motif discovery on multivariate wavelet-based signals,
  - identify candidate local patterns,
  - consolidate nearby patterns in time/scale into one event instance,
  - define risk at the event level rather than the pattern level.

Thank you for listening!

This presentation is based on the following working paper:

Lee, J., Badescu, A.L. and Lin, X.S. (2026). "A portfolio-anchored frequency–severity behavioral risk index for trip and driver assessment using telematics signals".

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