Wavelet-Based Driver Behaviour Classification for Smart-City Mobility

Michele Mastroianni*, Marco De Santis†, Lerina Aversano*
Simona Merola‡, Adrian Irimescu‡, Christian Esposito†
*University of Foggia, Foggia, Italy
†University of Salerno, Fisciano, Italy
‡National Research Council, Institute of Motors, Naples, Italy

***Abstract*—Smart cities require mobility services that are not only connected and data-driven, but also able to reduce energy demand and local emissions under real operating conditions. In this extended abstract we present the next step of a research line on driver-behaviour-aware control modules developed within the PRODIGI project. While previous work investigated Support Vector Machines and a comparative set of classical supervised classifiers, the proposed study introduces a wavelet-based representation of vehicle dynamics to identify aggressive and cautious driving behaviours. By decomposing speed- and acceleration-related signals in the time–frequency domain, the method is designed to capture short transients, oscillations, and multi-scale patterns that are usually smoothed out by purely statistical features. The expected outcome is a lightweight classification pipeline suitable for embedded control units and for integration with smart-road and connected-vehicle infrastructures.**

***Index Terms*—Smart cities; intelligent transportation systems; driver behaviour; wavelet transform; connected mobility; embedded machine learning.**

I. Introduction

The digital transformation of urban environments is fostering the development of Smart Cities where data-driven services continuously improve sustainability, mobility, safety, and quality of life. Among the various application domains, Intelligent Transportation Systems (ITS) and Cooperative ITS (C-ITS) play a fundamental role in enabling safer and more efficient mobility ecosystems. Modern vehicles continuously generate large amounts of information through onboard sensors, Electronic Control Units (ECUs), and CAN-BUS ommunication networks. Such data can be exploited to extract behavioural patterns and support adaptive services including eco-driving assistance, intelligent fleet management, dynamic insurance policies, traffic prediction, and Vehicle-toEverything (V2X) communication systems.

In this landscape, Driver Behaviour Classification has become a fundamental enabling process for intelligent transportation systems, as it provides actionable insights into driving patterns that can be leveraged to improve road safety, optimize traffic management, enhance energy efficiency, and support personalized mobility services in connected and smart urban environments.

This paper starts from the outcomes of the PRODIGI research project (PROcessi decisionali DIGitalizzati per una propulsione ad Idrogeno efficiente ed efficace), funded under the Italian National Recovery and Resilience Plan (NRRP) and completed last year, whose broader objective is the development of intelligent decision-making processes for future mobility platforms.

The previous studies conducted [1] [2] investigated machine learning approaches for driver behaviour classification and adaptive vehicle control. Building upon these results, the present work focuses on a novel signal-processing perspective based on Wavelet Transform techniques.

In fact, unlike traditional statistical approaches, wavelets enable simultaneous analysis in both time and frequency domains, making them particularly suitable for non-stationary signals such as vehicle telemetry. The proposed methodology aims at exploiting these properties to improve the characterization of driving styles and support future Edge AI services within connected urban mobility ecosystems.

II. Proposed Approach

The Wavelet Transform decomposes a signal into components associated with different frequency bands and temporal resolutions. This property makes wavelets particularly suitable for analysing non-stationary signals, such as those generated by vehicle dynamics during real-world driving. So, the proposed framework applies Discrete Wavelet Transform (DWT) to selected driving signals. Multi-scale decomposition allows the extraction of both low-frequency trends and high-frequency transient events associated with aggressive manoeuvres. Statistical descriptors are computed from approximation and detail coefficients and used as input features for the classification stage.

The adoption of Wavelet Transform offers several advantages:

- simultaneous time-frequency analysis;
- effective representation of non-stationary signals;
- identification of abrupt driving events;
- robustness against measurement noise;
- suitability for Edge AI implementations.

However, some limitations must also be considered: performance level strongly depends on wavelet family selection, and feature extraction introduces additional computational overhead.

The proposed workflow is shown in Fig. 1: in the first step, the vehicle dynamic signals, including speed, acceleration, and derived quantities such as jerk and power-demand proxies,

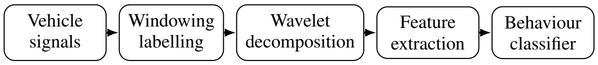

Fig. 1. Principle pipeline for wavelet-based driver behaviour classification.

have collected during real driving. A physics-based labelling stage assigns each time window to a cautious or aggressive class, following the rationale adopted in our previous work [2].

Instead of describing each window only through global statistics, we apply discrete wavelet transform (DWT) and wavelet packet decomposition to obtain multi-resolution coefficients. Given a signal $x(t)$, the continuous wavelet transform is

$$W_x(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t)\, \psi^* \left(\frac{t-b}{a} \right) dt, \tag{1}$$

where a is the scale, b the translation, and ψ the mother wavelet. In the discrete case, approximation and detail coefficients can be computed as

$$a_j[k] = \sum_n h[n-2k] a_{j-1}[n], \quad d_j[k] = \sum_n g[n-2k] a_{j-1}[n], \tag{2}$$

with h and g denoting low-pass and high-pass filters. These coefficients separate low-frequency trends, associated with route and traffic conditions, from high-frequency components, associated with sudden throttle/brake actions and stop-and-go dynamics.

The choice of particular ML technique to use focuses on four criteria: classification performance, robustness across trips, inference latency, and memory footprint. This is essential because the final target is not an offline analytics dashboard, but an embedded module able to adapt control parameters in real time or near real time. From the wavelet domain we extract compact descriptors such as sub-band energy, entropy, coefficient variance, and ratios between detail and approximation components. These features are then used to train and compare lightweight classifiers, such as SVM, Random Forest, Gradient Boosting, and Logistic Regression.

For conduct the experiments, we use the HCRL Driving dataset[1] [3], built recording data from real vehicles. The dataset includes 51 different features sourced by CAN-BUS car devices, associated with the conditions of the vehicle, and the data consists in 94,401 records recorded every second with the size of 16.7Mb in total.

III. Smart-City Relevance

The proposed classifier can act as a human-in-the-loop sensing layer for smart mobility. At vehicle level, it can support adaptive calibration by selecting control maps that better match the current driving style. At infrastructure level, aggregated and anonymised behaviour indicators can enrich smart-road services, eco-driving feedback, and fleet-management platforms. In connected-to-everything scenarios, a city may combine traffic-light timing, congestion information, and driver-style estimation to reduce unnecessary transients, thereby improving energy efficiency and comfort without imposing fully automated control.

Compared with previous SVM-only and classifier-comparison studies, the wavelet representation is expected to be more suitable for urban trips, where informative events are short, non-stationary, and distributed over multiple time scales. In other words, the proposed approach uses data already available in connected vehicles and transforms it into actionable intelligence for sustainable urban mobility.

[1] Available at https://ocslab.hksecurity.net/Datasets/driving-dataset

IV. Expected Contribution and Work Plan

The study will deliver: (i) a wavelet-based feature-extraction module for driver behaviour classification; (ii) an experimental comparison with time-domain baselines from related work, and (iii) an analysis of computational cost for embedded deployment. The final validation will consider both machine-learning metrics, such as accuracy, F1-score, and confusion matrices, and engineering metrics, such as inference time and feature-vector size.

The main expected result is a classification pipeline that preserves the accuracy of state-of-the-art supervised models while improving the interpretability of aggressive events through time–frequency features. This will support the design of behaviour-aware control modules for connected vehicles and provide a reusable ICT component for low-emission, connected smart-city transportation.

References

[1] M. Mastroianni, S. Merola, A. Irimescu, M. D. Santis, C. Esposito, and L. Aversano, "An SVM-based approach to develop a new control module for H2-powered engine using driver behaviour classification," SAE International, Tech. Rep. 2025-32-0042, 2025.

[2] M. D. Santis, A. Irimescu, L. Aversano, M. Mastroianni, S. Merola, and C. Esposito, "Using driver behavior classification to implement an H2-powered motor control system," *Journal of Physics: Conference Series*, vol. 3143, no. 1, p. 012092, 2025.

[3] B. I. Kwak, J. Woo, and H. K. Kim, "Know your master: Driver profiling-based anti-theft method," in *2016 14th Annual Conference on Privacy, Security and Trust (PST)*. IEEE, 2016, pp. 211–218.

[4] S. G. Mallat, "A theory for multiresolution signal decomposition: The wavelet representation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 11, no. 7, pp. 674–693, 1989.

[5] I. Daubechies, *Ten Lectures on Wavelets*. Philadelphia, PA, USA: SIAM, 1992.

[6] C. M. Martinez, M. Heucke, F.-Y. Wang, B. Gao, and D. Cao, "Driving style recognition for intelligent vehicle control and advanced driver assistance: A survey," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 3, pp. 666–676, 2018.

[7] A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi, "Internet of things for smart cities," *IEEE Internet of Things Journal*, vol. 1, no. 1, pp. 22–32, 2014.

[8] L. Eboli, G. Mazzulla, and G. Pungillo, "Combining speed and acceleration to define car users' safe or unsafe driving behaviour," *Transportation Research Part C*, 2016.

[9] S. Ullah and D.-H. Kim, "Lightweight driver behavior identification model with sparse learning on in-vehicle CAN-BUS sensor data," *Sensors*, 2020.

[10] F. Martinelli, F. Mercaldo, A. Orlando, V. Nardone, A. Santone, and A. K. Sangaiah, "Human behavior characterization for driving style recognition in vehicle system," *Computers Electrical Engineering*, vol. 83, p. 102504, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0045790617329531