A Novel Framework for Detecting Dangerously Slow Vehicle on Highway Corridor in a Partially Connected Environment

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Introduction

- Slow Vehicles in free flow conditions are affecting the global driving safety with required maneuvers for other drivers, like « mandatory lane changes ». We assume that such behaviour should affect the natural spatial distribution of lane-changes and be featued by a recognizable pattern.

- **Main contributions :**
  - Introduction of a **lane change detection process with low requirements regarding the input data**, only requirement: the speed and heading time-series of Connected Vehicles (CVs) natively left by CVs through Cooperative Awareness Messages.
  - Introduction of a **slow vehicle detection process** based on the **weighted local density of lane changes** along a highway.

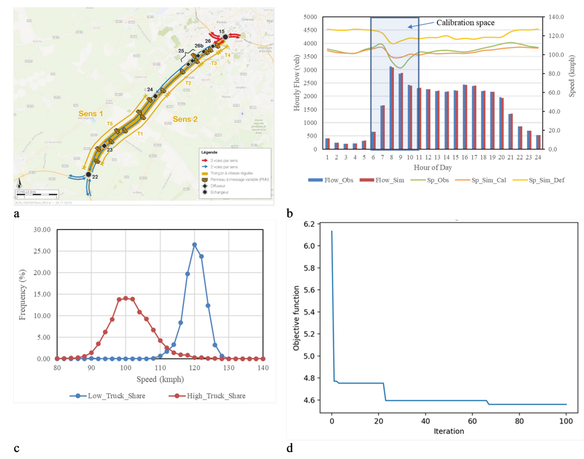
Experimental context

A fully simulated framework

- **SUMO [1]** is implemented with the default lane-change model [2] and a Krauss [1] car-following model calibrated thanks to a Genetic Algorithm.
- **TraCI** is used to dynamically collect data on Connected Vehicles with a refreshment period of 10 Hz.

TABLE 1: Default and calibrated values of selected parameters

Parameter	Default Value	Calibrated Value	
		CAR	TRUCK
maxSpeed (m/s)	36.11	32.2	26.4
minGap (m)	2.5	2.4	3.15
accel (m/s^2)	2.6	2.5	
decel (m/s^2)	4.5	4.65	
sigma	0.5	0.7	0.75
tau (s)	1	1.3	1.5



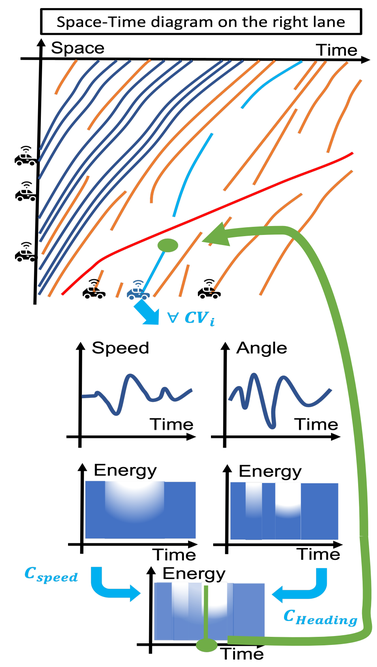
Methodology

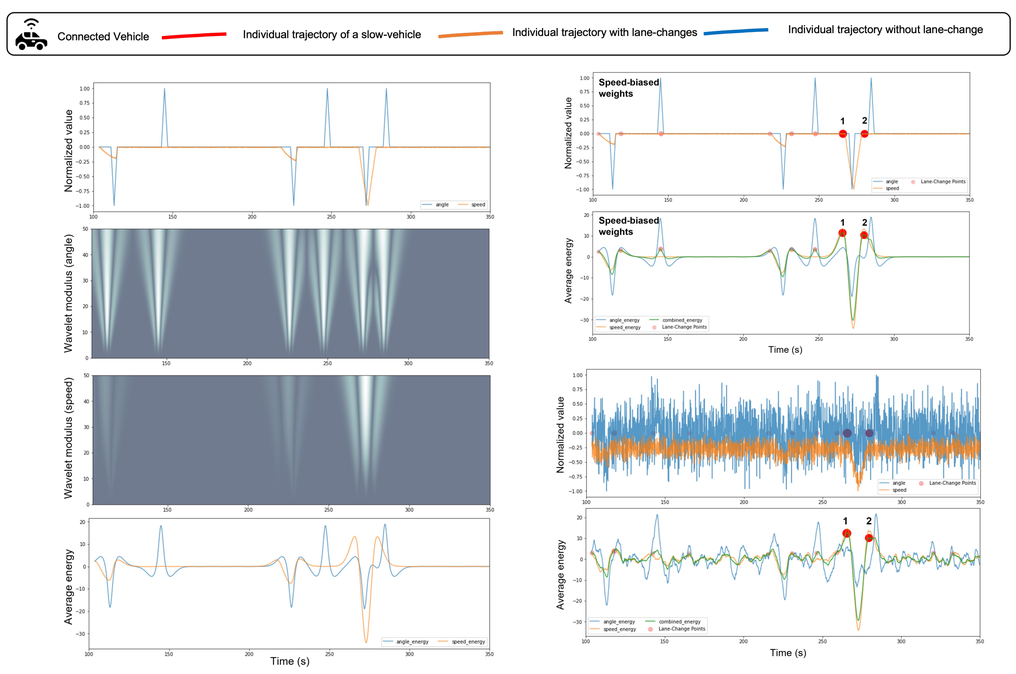
Step 1: Detecting lane-changes based on modifications of CV's energy computed by Wavelet Tranform

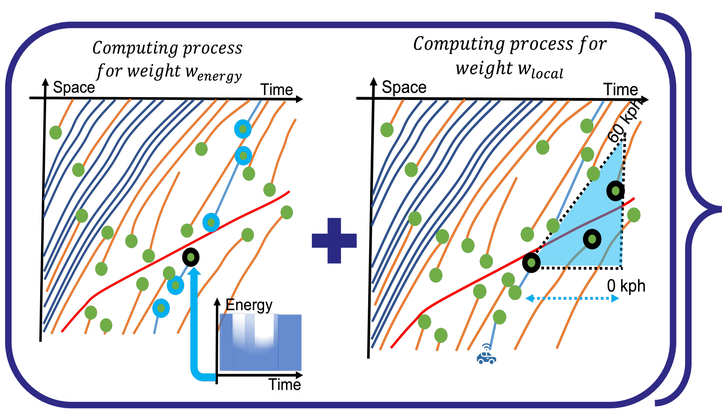
- For a fixed time-window (60s long, updated every 30s),
  - For any Connected Vehicles (CVs),
    - The speed and steering angle profiles of Connected Vehicles (CVs) are collected and feed a Wavelet Transform (WT) analysis.
    - The energy resulting from the WT of speed and steering angle is combined into a global indicator E^{global}.

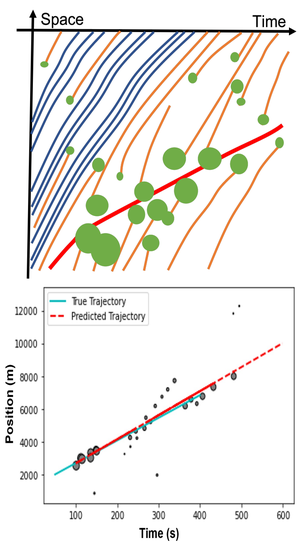
$$\forall b, \quad E^{global}(b) = C_{speed} \times E^{speed}(b) + C_{angle} \times E^{angle}(b)$$

- The global indicator E^{global} is compared to a threshold, when it is larger than 2.5, a lane-change is detected.









Step 2: Scatter plot analysis for slow-vehicles detection

- Preliminary identified lane-changes are discriminated by computing two weights aiming at reinforcing the distinction between patterns related to slow-vehicles and other lane changes
  - A weight related to the average WT energy
  - A weight related to the local density of lane-changes
- A (combination of) Gaussian (Weighted) Linear Regression is then applied to approximate the potential trajectory of the slow vehicle and threshold-based criterion are set up to validate the existence of a slow vehicle.

A 2-levels Gaussian Linear Regression based algorithm

Algorithm 1 Slow vehicle detection process algorithm

Require: WeightedScatterPlot

```
WLROuput ← WLR(WeightedScatterPlot)
                                  ▷ Apply LR with weighted samples
if WLROuput.Adjusted R^2 ≥ 0.9 then
                                  ▷ Check that WLR fit properly
    SlowVehicleSpeed ← WLROuput.SlopeCoefficient
                                  ▷ Collect speed estimation
    SlowVehicleInitialPosition ← WLROuput.InterceptCoefficient
                                  ▷ Collect initial position estimation
else
    Errors ← WLROuput.residuals
                                  ▷ Collect residuals errors from WLR
    MedError ← median(Errors)
                                  ▷ Calculate the median residual error
    SubsetScatterPlot ← WeightedScatterPlot [ Errors ≤ MedError ]
                                  ▷ Select only points with error lower than the median error
    LROutput ← LR(SubsetScatterPlot)
                                  ▷ Apply Linear Regression to the subset
    SlowVehicleSpeed ← LROuput.SlopeCoefficient
                                  ▷ Collect speed estimation
    SlowVehicleInitialPosition ← LROuput.InterceptCoefficient
                                  ▷ Collect initial position estimation
end if
if SlowVehicleSpeed ≤ 60 km/h then
    SlowVehicleStatus ← True
else
    SlowVehicleStatus ← False
end if
    return {SlowVehicleStatus, SlowVehicleSpeed, SlowVehicleInitialPosition}
```

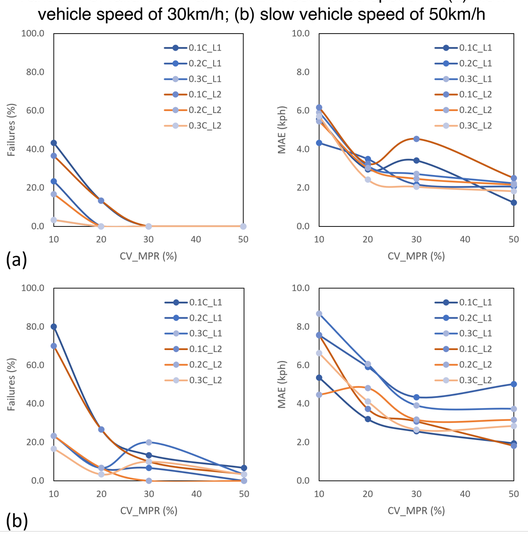
Main results

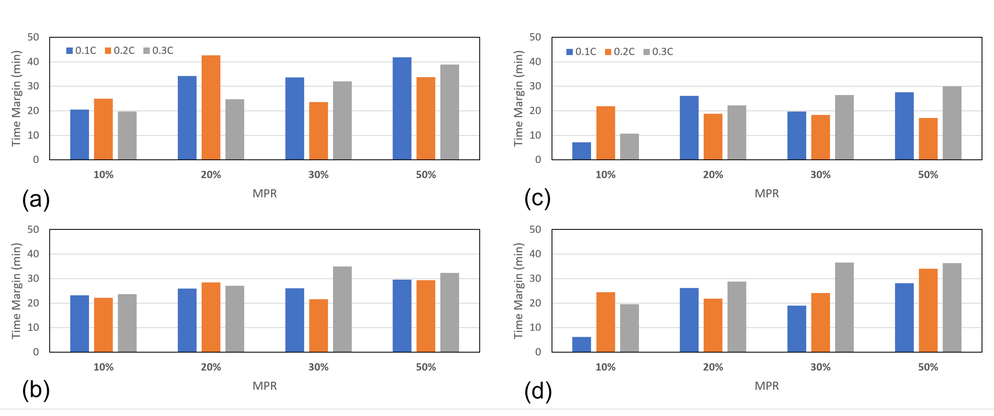
Experimental Design

- **Parameters under consideration**
  - Volume-to-Capacity ratio: 10%, 20%, 30%
  - CVs Market Penetration Rate: 10%, 20%, 30%, 50%
  - Speed of the slow vehicle: 30 kph, 50 kph
- Any unique combination of parameters was computed with 30 random seeds for stochasticity purpose

- **Key Performance Indicators**
  - Failure Rate
  - Mean Absolute Error (MAE) of Estimated Speed of Slow Vehicle
  - Time Margin for Warning

Variation of failure rate and MAE of estimated speed for (a) slow vehicle speed of 30km/h; (b) slow vehicle speed of 50km/h





Variation of time margin over different market penetration of CV and flow levels for (a) slow vehicle speed of 30km/h and level 1 regression; (b) slow vehicle speed of 30km/h and level 2 regression; (c) slow vehicle speed of 50km/h and level 1 regression; (d) slow vehicle speed of 50km/h and level 2 regression

Conclusions and Highights

- The **performance** of the slow vehicle detection algorithm **stabilizes** at **a market penetration of 30**% which emphasizes that a high market penetration might not be necessary for deployment ;
- Globally, the **MAE** is **below 6km/h and 8km/h** for slow vehicle speeds of 30km/h and 50km/h respectively ;
- Because with a slow vehicle driving at 50 kph, its speed is **closer to the flow's speed**, the **failure rate is higher** ;
- Mostly, the 2-levels regression outperforms the 1-level in terms of reduced failure rates and estimated errors.

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[3] Zheng, Z., S. 1 Ahn, D. Chen, and J. Laval, Applications of wavelet transform for analysis of freeway traffic: Bottlenecks, transient traffic, and traffic oscillations. Transportation Research Part B: Methodological, Vol. 45, No. 2, 2011, pp. 372–384.