Intelligent Speed Advising Based on Cooperative Traffic Scenario Determination

Rodrigo H. Ordóñez-Hurtado, Wynita M. Griggs, Kay Massow and Robert N. Shorten

Abstract A novel system for safe speed recommendation, based on a cooperative method for vehicular density estimation and on the intelligent determination of the traffic scenario, is presented.

1 Introduction

At present, Intelligent Speed Adaptation (ISA) systems, as a part of Advanced Driver Assistance Systems (ADASs), have become a fundamental part in the designing of safe vehicle operation systems, with the aim of improving driver/pedestrian safety using environmentally friendly applications [1]. Statistically, ISA systems always represent an improvement in the reduction of CO_2 emissions and fuel consumption, and on saving/prediction of accidents (fatal, serious and slight) [1]. Advisory systems rely on the calculation of safe recommended parameters to be presented to the driver using an appropriate display system [2]. Thus, in general, advisory ISA methodology involves less algorithmic and analytical complexity, and constitutes the first step towards more comprehensive (mandatory) systems, and the enhancement of Adaptive Cruise Control (ACC) algorithms [3]. ISA systems can be greatly improved by including relevant information from different sources such as environmental (weather, visibility, etc) and road (vehicular density, speed limits, etc) information, thus resulting in more reliable systems [4]. A recent application based on weather information can be found in [5]. Regarding road information, vehicular density represents a very important factor in designing systems for safe speed

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advising, because from it, it is possible to obtain a more realistic awareness of the general traffic situation [6]. In this sense, most ADASs involving vehicular density estimation techniques are based on the use of loop detectors [7, 8]. However, there are many drawbacks in using this kind of dedicated infrastructure device: 1) vehicular density is computed only for fixed road sections (between two consecutive loop stations), i.e. the available information is space-discontinuous; and 2) density variations cannot be properly detected at each location with a low density of loop detector stations (but a high density of them is not desirable from the monetary point of view) [7]. Moreover, if we think in terms of a decentralised scheme, then vehicular density should be estimated for each node belonging to the vehicular ad-hoc network (VANET), making even less feasible the use of loop detectors. Thus, more practical ways to estimate vehicular (traffic) density are required, such as the one presented in [6]. With the above in mind, we propose a two-stage methodology for intelligent speed advising: the first stage concerns traffic scenario determination based on a cooperative methodology using vehicle-to-vehicle (V2V) communication for vehicular density estimation, and a rule-based system (Section 4), and the second stage concerns the calculation of safe parameters based on the proposed traffic scenario determination (Section 5). Experimental validation is presented in Section 6, and we conclude the paper with Section 7.

2 Intelligent Speed Adaptation System

ISA systems can be classified as either static or dynamic. A static ISA system is a system where the recommender is supported only on fixed/localised speed limits, whereas a dynamic ISA system also uses environmental information to update the recommended speed. ISA systems can also work in advisory, voluntary or mandatory modes. In an advisory mode, the function of the ISA is to recommend a speed to the driver, and in mandatory mode a control action is used to enforce the advised speed. For dynamic-mandatory cases it has been shown that ISA systems are able to provide safety benefits in terms of a reduction of up to 44% in fatality [5]. Recent developments in ITS infrastructure have made possible the development of more advanced ISA systems. In this paper we describe one such a system. Our system allows the inclusion of relevant available information using current traffic information and road speed limits for calculating the recommended speed. We propose to use V2V communication as a main tool for vehicular density calculation rather than loop detectors, with the aim of obtaining space-continuous information through a cheaper approach (as opposed to using dedicated infrastructure devices). Consequently vehicular density is used as one of the inputs of a rule-base reasoning engine designed to determine the current traffic scenario; the scenario that will be used to dynamically calculate the final recommended speed. The main advantage of using such an inference engine is the possibility of including expert knowledge in an easy and intuitive way via IF-THEN rules. Finally, we assess our speed adaptation scheme using a traditional safe policy applied to the resulting inter-vehicle distances.

3 Procedure

We are proposing a two-stage methodology for intelligent speed advising: a) the first stage focuses on traffic scenario determination, and b) the second stage regards safe parameters calculation. In the first stage we consider the problem from a spatial-temporal perspective. We begin this process by defining a point of reference that represents a point along the future trajectory of the vehicle for which the recommender is being constructed. Thus, the following concepts arise:

- the *Host Vehicle* (HV) is the vehicle for which the recommendation is being constructed.
- the *Next Point of Interest* (NPI) is a coordinate in the near future of the Host Vehicle's evolution, i.e. a point located in the future trajectory of the Host Vehicle.
- the *Next Vehicle* (NV) is the (potentially virtual) vehicle that is currently closest to the NPI.

Once the Next Vehicle has been selected, the calculation of the vehicular density is obtained as the vehicle density in some prespecified area around the NPI. Due to the spatial-temporal nature of the problem, vehicular density is calculated for both the Host Vehicle and the NPI.

The current traffic scenario is determined by using the calculated vehicular density and speed for both the Host and Next Vehicles, and the variation of the Host Vehicle speed as the inputs of an inference engine. Our inference engine is made up by a set of 28 IF-THEN rules.

For the second stage of the procedure, we propose to calculate the recommended speed using a weighted formula that combines both the Host and Next Vehicle speeds, as well as density information.

Finally, once the recommended speed is obtained, we use a widely known policy for safe recommended distance.

For ease of exposition, we make the following assumptions:

- our road setup is as depicted in Fig. 1:
  - a five-section (S1-S5), two-lane (L1-L2), one traveling direction straight road;
  - a 2D Cartesian system for spatial representation of the road (top view) where the x axis is the direction of travel;
  - a stationary bottleneck represented by the narrowing of the road (S3), emulating a closed lane e.g. due to an on-road accident;
- and

A1 all vehicles belonging to the VANET have a compatible V2V system;
A2 all required information can be acquired using suitable devices/techniques, and then transmitted using such a V2V system;
A3 processing times for V2V communication and outputs calculation are greatly shorter than intervals between instants for speed recommendation.

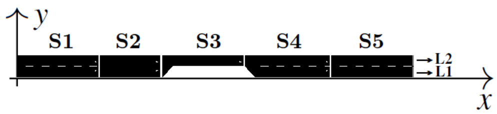


Fig. 1 Road setup used.

4 Methodology: First Stage

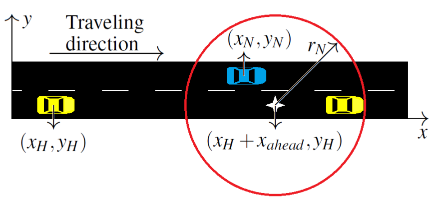
In the first stage of the proposed ISA methodology, the basic idea is to use V2V communication to obtain an estimation of the vehicular density. With such information, in addition to speed values and other relevant data, we determine the current traffic scenario using a rule-based system.

However, as the traffic scenario determination is a spacial-temporal problem, other sources of information must be considered in addition to the Host Vehicle information. This demands the selection of a vehicle placed at a point in the ahead road-section in which the Host Vehicle is traveling on, in order to represent a point along the future trajectory of the Host Vehicle. Hereafter, such a point is the NPI, and the vehicle representing the NPI will be referred to as the Next Vehicle (which is not necessarily the vehicle immediately preceding the Host Vehicle).

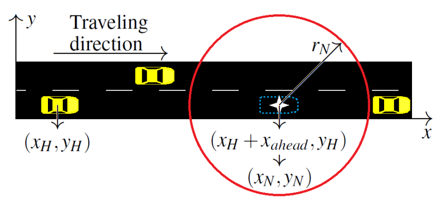
4.1 Selection of the Next Point of Interest and the Next Vehicle

The NPI is a reference placed at a distance x_{ahead} in front of the Host Vehicle. As we are considering a straight road collinear to the x axis, we define the NPI at $(x_H + x_{ahead}, y_H)$, where (x_H, y_H) is the position of the Host Vehicle.

In order to select the Next Vehicle to represent the NPI, we look inside a circle with radius r_N centered at $(x_H + x_{ahead}, y_H)$ as shown in Fig. 2. If no vehicles are inside the circle (see Fig. 2b), then we let the Next Vehicle be a virtual vehicle located at $(x_N, y_N) = (x_H + x_{ahead}, y_H)$; otherwise the closest vehicle to the NPI is selected (see Fig. 2a).



(a) Vehicles inside of r_N



(b) No vehicles inside of r_N.

Fig. 2 NPI location: a) the Next Vehicle is the nearest vehicle to $(x_H + x_{ahead}, y_H)$, i.e. the blue one, and b) the Next Vehicle is a virtual vehicle located at $(x_H + x_{ahead}, y_H)$.

4.2 Vehicular density estimation

The vehicular density estimation for any sampling node in the VANET can be carried out based on [7], as follows: 1) the sampling node broadcasts a poll message, 2) all nodes receiving the poll message respond to the sampling node with a reply message, and 3) vehicular density δ for the sampling node is given by

$$\delta(t) = \frac{n_r + 1}{A}, \qquad A = \begin{cases} \pi r_D^2, & \text{if } 2r_D \leq W_R = W_L N_L. \\ 2r_D W_L N_L, & \text{otherwise.} \end{cases},$$

where n_r is the number of returned replies inside the polling area A, W_R is the road's width, W_L is the lane's width, and N_L the total amount of lanes. Note that the factor $+1$ is added to the factor n_r to include the sampling node into the density equation. However, if the sampling node is a virtual vehicle, then the vehicular density is not $\frac{1}{A}$ but rather zero (see Fig. 2b).

4.3 Traffic scenario determination

Once the vehicular density for both Host/Next Vehicles is calculated, we can use that information in addition to the Host/Next Vehicle speeds in order to determine the traffic scenario. In this paper we proposed to use an inference engine for that purpose, as explained in the following subsections.

4.3.1 Inference engine design

The inference engine consists of a (user-defined) knowledge base for assigning values to the outputs according to the values of the inputs. Let us define the inputs/outputs variables, to latter define the base of rules that relates them.

Inputs/outputs definition

Five variables are chosen as inputs: the normalised Host Vehicle's velocity ($\bar{V}_H$); the normalised Next Vehicle's velocity ($\bar{V}_N$); the normalised vehicular density for the Host Vehicle ($\bar{\delta}_H$); the normalised vehicular density for the Next Vehicle ($\bar{\delta}_N$); and the variation on the Host Vehicle's velocity $\Delta V_H(t) = V_H(t) - V_H(t-1)$. In addition, five variables are chosen as outputs: Free Traffic (FT); Approaching Congestion (AC); Congested Traffic (CT); Passing Bottleneck (PB); and Leaving Congestion (LC).

The sets Low (L) and High (H) are for the inputs $\bar{V}_{H,N}$ and $\bar{\delta}_{H,V}$, the sets Negative (N), Zero (Z) and Positive (P) are for the input $\Delta V_H(t)$, and the sets Not (N) and Yes (Y) are for all the outputs. Membership functions are shown in Table 1.

Finally, the traffic scenario is classified according to the following equation:

$$T(t) = \text{argmax}(\text{FT}(t),\text{AC}(t),\text{CT}(t),\text{PB}(t),\text{LC}(t)).$$

Table 1 Membership functions.

Type	Variable	Set	Membership function
Input	$\bar{V}_{H,N}, \bar{\delta}_{H,V}$	L	[0 0 0.1 0.8]
		H	[0.1 0.8 1 1]
	$\Delta V_H(t)$	N	[-100 -100 -7.5 -2.5]
		Z	[-7.5 0 7.5]
		P	[2.5 7.5 100 100]
Output	FT,AC,CT,PB,LC	N	[0 0 1]
		Y	[0 0.8 1 1]

Table 2 Base of rules for traffic scenario determination.

Rule	Inputs		Outputs	
	$[\bar{V}_H, \bar{\delta}_H, \bar{V}_N, \bar{\delta}_N]$	ΔV_H	[FT, AC, CT, PB, LC]	WEIGHT
1	[L,L,L,L]	N	[Y,N,N,N,N]	0.6
2		Z	[Y,N,N,N,N]	0.6
3		P	[N,N,N,N,Y]	1.0
4	[L,L,L,H]	-	[N,Y,N,N,N]	1.0
5	[L,L,H,L]	N	[Y,N,N,N,N]	1.0
6		Z	[N,N,N,N,Y]	1.0
7		P	[N,N,N,N,Y]	1.0
8	[L,L,H,H]	-	[N,Y,N,N,N]	1.0
9	[L,H,L,L]	N	[N,N,Y,N,N]	1.0
10		Z	[N,N,N,Y,N]	1.0
11		P	[N,N,N,Y,N]	1.0
12	[L,H,L,H]	-	[N,N,Y,N,N]	1.0
13	[L,H,H,L]	-	[N,N,N,Y,N]	1.0
14	[L,H,H,H]	-	[N,N,Y,N,N]	1.0
15	[H,L,L,L]	N	[N,Y,N,N,N]	1.0
16		Z	[Y,N,N,N,N]	1.0
17		P	[Y,N,N,N,N]	1.0
18	[H,L,L,H]	-	[N,Y,N,N,N]	1.0
19	[H,L,H,L]	N	[Y,N,N,N,N]	1.0
20		Z	[Y,N,N,N,N]	1.0
21		P	[N,Y,N,N,N]	1.0
22	[H,L,H,H]	-	[N,Y,N,N,N]	1.0
23	[H,H,L,L]	N	[N,N,Y,N,N]	0.8
24		Z	[N,N,Y,N,N]	0.8
25		P	[N,N,N,Y,N]	1.0
26	[H,H,L,H]	-	[N,N,Y,N,N]	1.0
27	[H,H,H,L]	-	[N,N,N,Y,N]	1.0
28	[H,H,H,H]	-	[N,N,Y,N,N]	1.0

Base of rules

The rules R_k for relating the five inputs to the five outputs are of the form

$\underline{R_k}$: IF $input_1 = \bullet$ AND... $input_i = \bullet$, THEN $(output_1 = \bullet \text{ AND}... output_j = \bullet) * w_k$,

according to values in Table 2, which are supported by applying both traffic flow theory [9] and common sense to each particular case, and considering the values taken for each input.

4.3.2 Normalisation of variables

In order to provide a general interpretation of the rules, we use normalised values instead of raw ones. Such a normalisation process depends on each kind of input, as presented in the following subsections.

Velocity normalisation

This normalisation depends on the raw value of the velocity, the Maximum Individual Speed (MIS) of the vehicle, and the Road Speed Limit (RSL) of the road section in which the vehicle is traveling on. The normalised velocity is given by

$$\bar{V}_{H,N}(t) = \min\left(\alpha_{speed} * \tilde{V}_{H,N}(t), 1\right),$$

$$\alpha_{speed} = \frac{1}{\max\left(MIS_{H,N}, RLS_{H,N}\right)}, \quad \tilde{V}_{H,N}(t) = \begin{cases} V_{H,N}(t), & \text{if } MIS_{H,N} > RLS_{H,V} \\ f_1\left(RLS_{H,V}, MIS_{H,N}, V_{H,N}(t)\right) & \text{otherwise.} \end{cases},$$

where f_1 provides a value corresponding to the linear interpolation of the $V_{H,N}(t)$ using a curve given by $\{(0, RLS_{H,V}), (0, MIS_{H,N})\}$. Note that $\min(\bullet, 1)$ ensures that the maximum value of $\bar{V}_{H,N}(t)$ is 1 even when the velocity overcomes the corresponding *RLS*.

Vehicular density normalisation

This normalisation depends on the raw value of the vehicular density, the polling radio r_D, and the Maximum Allowed Density (MAD) curve (constructed from Table 3). The normalised vehicular density can be calculated as

$$\bar{\delta}_{H,N}(t) = \min\left(\alpha_{density} * \delta_{H,N}(t), 1\right), \qquad \alpha_{density} = \frac{1}{f_2(r_D)},$$

where the value of $f_2(r_D)$ (representing the MAD given r_D) is calculated according to a linear interpolation using data in Table 3 (obtained from simulation tests).

Again, $\min(\bullet, 1)$ assures that the maximum value of $\bar{\delta}_{H,N}(t)$ is 1 even when the vehicular density overcomes the corresponding estimated MAD.

Table 3 Maximum allowed density (f_2) given r_D.

r_D	7.5	8.5	9.5	11	13	15	19.5	21
$f_2(r_D)$	7	6	5.5	5	4.5	4.2	3.9	3.8

5 Methodology: Second Stage

Once the traffic scenario is determined, we can use such information to design our Advisory ISA methodology. However, since the definition of the recommended speed V_R (and as a consequence, the recommended distance D_R) should be based upon both the determined traffic scenario and the Next Vehicle's velocity (V_N), then we first introduce a model for updating V_N in cases of a virtual Next Vehicle.

5.1 Updating speed in virtual Next Vehicles

If a virtual Next Vehicle is chosen, then both the location and velocity of the Next Vehicle have to be calculated from other sources rather than a real vehicle on the road. Recall that we already assigned the location of such a virtual Next Vehicle as $(x_H + x_{ahead}, y_H)$ (see Subsection 4.1), but a model for its velocity updating is still missing. Thus, we propose a way to update V_N similar to

$$V_N(t) = \alpha_{NV}(t) * V_N(t-1),$$

where $\alpha_{NV}(\bullet)$ is the evolution parameter, but including some particular considerations. Our way for updating the normalised virtual Next Vehicle speed $\bar{V}_N$ is then given by

$$\bar{V}_N(t) = \min\left(\alpha_{NV}(T(t-1)) * f\left(\bar{V}_N(t-1)\right), 1\right), \tag{1}$$

$$f\left(\bar{V}_N(t-1)\right) = \max\left(\bar{V}_N(t-1), \underline{V}_N(T(t-1))\right), \tag{2}$$

where $T(\bullet)$ is the determined traffic scenario, and $\underline{V}_N(\bullet)$ is the minimum allowed normalised speed for a virtual Next Vehicle. The inclusion of this minimum limit speed, which is greater than zero, is to avoid $\bar{V}_N = 0$ which represents that the Host Vehicle is approaching a stopped vehicle, which is not true because there are no real vehicles around the NPI (see Fig. 2). Then, $\min(\bullet, 1)$ in (1) is to guarantee that $\bar{V}_N$ never exceeds the maximum normalisation value 1, and $\max(\bullet, \underline{V}_N(\bullet))$ in (2) is to guarantee that the virtual Next Vehicle is always moving at least at $\underline{V}_N$. Both α_{NV}

and $\underline{V}_N$ are design parameters, and reference values (obtained from simulation tests) are given in Table 4.

Table 4 Decision matrix for $\underline{V}_N$, α_{NV} and α_R.

Traffic scenario	FT	AC	CT	PB	LC
Value of $\underline{V}_N$	0.3	0.2	0.1	0.1	0.3
Value of α_{NV}	1.4	0.7	0.9	0.9	1.4
Value of α_R	0.7	0.7	0.7	0.45	0.7

Justification for values in Table 4 are as follows:

- Given previous *Free-Traffic/Leaving-Congestion* scenarios, it is assumed that the virtual Next Vehicle can accelerate without problems. Thus, α_{NV}=1.4 represents an increase of 40% in V_N, and $\underline{V}_N$=0.3 sets a minimum value for $\bar{V}_N$ at 0.3.
- Given previous *Congested-Traffic/Passing-Bottleneck* scenarios, it is assumed that the virtual Next Vehicle could not have accelerated, and probably could have had a small deceleration. Thus, α_{NV}=0.9 represents a decrease of 10% in V_N, and $\underline{V}_N$=0.1 sets a minimum value for $\bar{V}_N$ at 0.1.
- Given a current *Approaching-Congestion* scenario, it is assumed that the virtual Next Vehicle is indeed decelerating. Thus, α_{NV}=0.7 represents a decrease of 30% in that V_N, and $\underline{V}_N$=0.2 sets a minimum value for $\bar{V}_N$ at 0.2.

5.2 Proposed recommended speed scheme

We propose a calculation method for the recommended cruise speed similar to the one presented in [5], i.e. a convex linear combination with time-variant coefficients. However, here we calculate the recommended speed by combining two terms, the Host Vehicle speed V_H and the Next Vehicle speed V_N, as follows

$$V_R(t) = (\alpha_R(T(t))) * V_N(t) + (1 - \alpha_R(T(t))) * V_H(t), \quad (3)$$

where $\alpha_R(\bullet)$ is a time-variant weighting factor calculated from the decision matrix presented in Table 4. Note that α_R is a design parameter, so values in Table 4 were tuned from simulation tests. The justification for values of α_R is as follows:

- *Approaching-Congestion/Congested-Traffic* scenarios should force the Host Vehicle to slow down in order to travel at most around V_N, which in general is a real vehicle inside a dense platoon immediately ahead of the Host Vehicle. Then, α_R=0.7 means that the recommended speed depends more upon V_N than V_H, causing V_N to act like an upper bound.
- *Free-Traffic/Leaving-Congestion* scenarios should force the Host Vehicle to speed up in order to reach V_N, which is expected to be traveling in a *Free-Traffic* scenario. Then, α_R=0.7 means that the recommended speed depends more upon V_N rather than V_H, causing V_N to act like a goal speed.

- The *Passing-Bottleneck* scenario is determined based on the existence of a Next Vehicle who is leaving the congestion with positive high ΔV_N. However, here the Host Vehicle is about to leave the traffic jam but is still inside it, so the recommended speed should depend more upon V_H than V_N. Then, α_R=0.45 causes V_H to act like an upper bound.

According to (3), it is observed that V_R always depends directly on both V_H and V_N, so any noisy behaviour in either of them will be directly reflected on V_R. Thus, two additional processes have to be added: 1) a quantisation process, to avoid a noisy recommended speed, and 2) a saturation process, to avoid recommending a speed greater than the speed limit of the road on which the Host Vehicle is traveling. With this we finally obtain $V_R \in \min\left(\{5*n\}, RLS_H\right)$, with $n = 1, 2, \ldots$.

5.3 Proposed recommended distance scheme

We can assess the performance of our recommended speed scheme by evaluating the usually adopted safe inter-distance policy [10]

$$D_R(t) = h_0 + h_1 V_f(t) + h_2 \left(V_f^2(t) - V_l^2(t)\right),$$

where D_R is the recommended (safe) distance, h_0 is the minimum safe distance to the preceding vehicle, h_1 is the minimal required headway time (usually set in h_s=0.6 $[s]$), h_2 is a problem-dependent weighting factor, V_f corresponds to the speed of the Host Vehicle, and V_l to the speed of the preceding vehicle. However, here the reference is the Next Vehicle, which does not necessarily coincide with the preceding vehicle. Thus, we have to take

$$V_l(t) = V_N(t),$$

and h_0 as the safe distance to the Next Vehicle, redefined as follows

$$h_0 = \left\lfloor \frac{X_N - (X_H + G_{min})}{L_V + G_{min}} \right\rfloor * (L_V + G_{min}) + G_{min},$$

where G_{min} is the minimum allowed gap (safe distance) between two consecutive vehicles, and L_V is the mean longitude of a vehicle in the network. Note that the *Approaching-Congestion*, *Congested-Traffic* and *Passing-Bottleneck* scenarios are of special interest, because only in these cases it is expected that there exists a high density of vehicles between the Host Vehicle and the Next Vehicle (i.e., a higher probability of collision).

Now, the recommended distance must be compared to the relative distance X_{rel}, measured as the difference between the Host Vehicle's position and the Next Vehicle's position

$$X_{rel} = X_N - X_H.$$

Then by defining $e{=}X_{rel}{-}D_R$, the case $e{\geq}0$ means that there is a safe situation (the relative distance is greater than or equal to the recommended distance), and thus the case $e{<}0$ means that there is a non-safe situation.

6 Validation

To validate the proposed methodology, we use SUMO to simulate thirty-one vehicles with properties as in Table 5, which travel according to a modified Krauss car-following model [11] on the road defined by Fig. 1 and Table 6. Vehicle 08 exhibits a special behaviour: it stops at $Distance{=}296\,[\mathrm{m}]$ (road section S4) for 100 seconds, after which it restarts its travel. The data obtained from SUMO was exported to the Matlab environment Version 7.12.0.635 (R2011a).

The idea behind using vehicles with very high deceleration abilities is to obtain data in extreme situations (i.e. the vehicles are very prone to having a collision), in order to evaluate the performance of the proposed methodology in recommending a safe speed early. In addition, speed restrictions on S2/S3 and S5 emulate realistic behaviours around a traffic bottleneck and the variety of piecewise constant speed limits along a same road, respectively.

Table 5 Properties of simulated vehicles used in tests.

Attribute	Vehicle Type		
	A	B	C
Vehicle's ID	03,09,11,13,15,17, 19,23,25,27,29,31.	04,05,07,10,12,14, 18,20,24,26,28.	01,02,06,08,16,21, 22,30.
Length [m]	4.4	4.0	4.2
Max Speed [m/s]	40	30	16.677
Acceleration [m/s^2]	3	2	1
Deceleration [m/s^2]	10	10	10
Minimum Gap [m]	2.5	2.5	2.5
Sigma	0.5	0.5	0.5

6.1 Traffic scenario determination

The inference engine was implemented using the FL Toolbox for use with Matlab [12], and tested using $r_N{=}4\,[\mathrm{m}]$, $r_D{=}14\,[\mathrm{m}]$, $x_{ahead}{=}32\,[\mathrm{m}]$, $W_L{=}3.5\,[\mathrm{m}]$ and $N_L{=}2$. The obtained results for vehicle number 20 are presented in Fig. 3 using the LOM (Last Of Maximum) method to calculate the outputs. With this method, all the estimations have a certainty value of 1.0 (i.e. complete certainty).

The traffic scenario determination for the entire set of vehicles is shown in Fig. 4a and Fig. 4b. From Fig. 4a, it can be concluded that almost all traffic scenarios

Table 6 Properties of road sections in Fig. 1.

Section	Length [m]	Max Speed [m/s]
S1	175	27.778
S2	5	0.7
S3	30	2.5
S4	235	27.778
S5	55	2.5

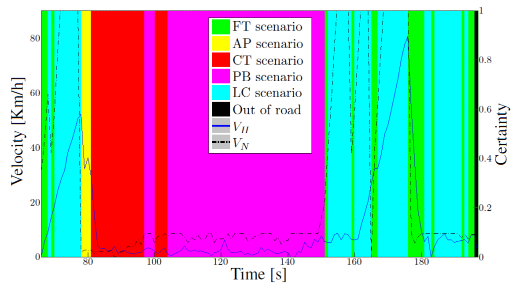
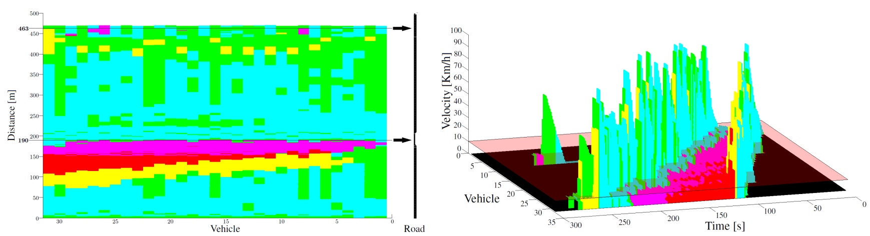


Fig. 3 Entire traffic scenario determination for vehicle 20 using LOM.

immediately below a cut at $Distance$=190 [m] (the medium point of the bottleneck) are determined as a *Passing-Bottleneck* scenario (magenta), and that some vehicles detect the new speed limit around $Distance$=463 [m] as a *Congested-Traffic* scenario (red) for a few seconds, just after the new speed limit's commencement at $Distance$=445 [m].



(a) Vehicle vs Distance (b) Vehicle vs Velocity vs Time

Fig. 4 Entire traffic scenario estimation for all vehicles using LOM.

For its part, Fig. 4b shows that most of the velocities beneath a cut at $Velocity$= 10 [km/h] are successfully classified as either *Passing-Bottleneck* or *Congested-Traffic* scenarios. Moreover, increasing velocities are suitably classified as either *Free-Traffic* scenario (green) or *Leaving-Congestion* scenario (cian), generally after *Passing-Bottleneck* or *Congested-Traffic* scenarios, as confirmed in Fig. 4a. Finally, decreasing velocities in Fig. 4b are successfully classified as an *Approaching-*

Congestion scenario (yelow) when a *Passing-Bottleneck* or *Congested-Traffic* scenario is about to occur (also confirmed in Fig. 4a).

6.2 Recommended speed

Results for the particular case of Vehicle 20 (Fig. 5) show that the critical *Approaching-Congestion* scenario is tackled properly by detecting the sudden (and maintained) decreasing of V_N at times 78 [s] and 177 [s] and then imposing an anticipated low V_R. With this, the Host Vehicle can be warned of the oncoming traffic jam early, and thus gains several seconds to perform a smoother braking action.

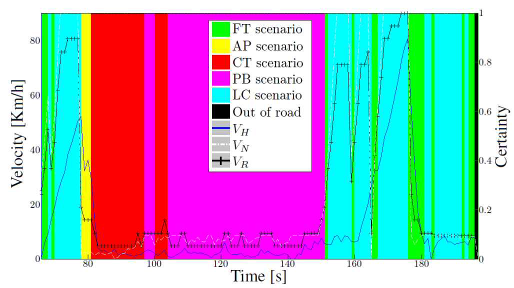
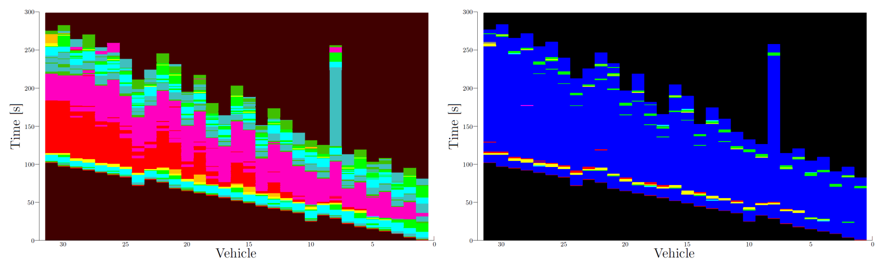


Fig. 5 Entire V_R profile for vehicle 20 using the proposed methodology.

Another sudden decrease in V_N occurs at 165 [s], and a low speed is recommended for a single instant. Such a decrease is not caused by any congestion, but by a stopped vehicle (Vehicle 08) in the middle of a *Free-Traffic* scenario. Then, the V_R profile is momentarily affected, indicating the existence of an isolated stopped vehicle (the estimated scenario remains as a *Free-Traffic* scenario during, and for some instants after, such a detection).

The performance of all vehicles can easily be analysed from Fig. 6 and Fig. 7 with a quick visual inspection, due to the colour-convention used: blue sections indicate that $V_R \geq V_H$. Note that the section for $V_R < V_H$ corresponding to the lower arrow in Fig. 7 exhibits a pattern that in general coincides with *Approaching-Congestion* scenarios, which can be explained as the approaching of the oncoming *Congested-Traffic*/*Passing-Bottleneck* scenarios with a suitable safe (low) speed. Two other cases in which $V_R < V_H$ also happen can be better understood from Fig. 7: the middle arrow indicates the detection of an isolated vehicle which is stopped in the middle of the road (Vehicle 08); and the upper arrow represents the case in which a segment of the road with a lower speed limit will be promptly reached.



(a) HV-speed/Traffic-scenario profiles.

(b) Prevalence of the V_R over V_H profile: Blue means $V_R > V_H$.

Fig. 6 Analysis of V_R for all vehicles in function of time. [Black sections: beyond road's length].

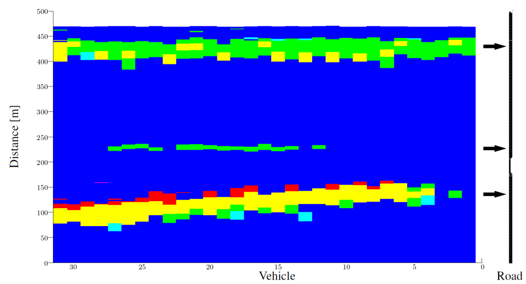


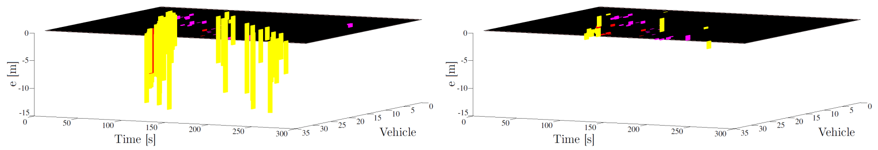
Fig. 7 Analysis of V_R for all vehicles in function of distance. Prevalence of the V_R profile over the V_H profile: blue means $V_R > V_H$.

6.3 Recommended distance

Our D_R scheme was tested with data from both:1) the original set-up (without taking into account V_R), and 2) the improved set-up (manual and isolated adjustment of the speed according to our V_R scheme) with $h_2=0.01$, $L_V=4.2$, and $G_{min}\,[\mathrm{m}]=2.5\,[\mathrm{m}]$.

In Fig. 8a (original setup) we can see that many of the $e<0$ cases are produced in *Approaching-Congestion* scenarios. This is particularly interesting because, there, V_H is much faster than V_N, producing large negative values for e (Fig. 8a), thus resulting in a high probability of collision. In Fig. 8b (improved setup) we can see that most of those dangerous situations are suitably tackled, and just a few of minor $e<0$ still remain.

Recall that in Cooperative ACC schemes the control law depends on the value of e [10]: the smaller e value, the weaker action control (breaking effort) in tracking the safety parameters. Thus, according to Fig. 8b, our recommended speed/distance schemes provide high performance in terms of travelling in safe conditions.



(a) X_{rel}, D_r obtained from $V_f = V_H$. (b) X_{rel}, D_r obtained from a V_f in function of V_R.

Fig. 8 3D analysis of $e = X_{rel} - D_r$ for all vehicles. Colored sections correspond to $e < 0$ (according the previous color convention).

7 Conclusions and Future Work

A new scheme for safe speed advising based on a cooperative and decentralised methodology for traffic scenario determination was proposed. Its performance was assessed using safe policies and supported by experimental tests via SUMO package. Currently, efforts are focused on evaluating the proposed ISA system beyond the used setup, i.e. using other realistic situations such as roads with curves and mobile bottlenecks.

An immediate future task is to use the proposed methodology to design a Cooperative ACC system by closing the speed/distance loops using the here proposed V_R and D_R schemes and a suitable controller. For such a mandatory ISA we have to be able to develop the corresponding analysis to guarantee string stability. In addition, other kinds of information can be used to improve the performance of the advisory system, such as meteorological (weather) and environmental (pollution) information.

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