Driving Information in a Transition to a Connected and Autonomous Vehicle Environment: Impacts on Pollutants, Noise and Safety

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Abstract

The main objective of this vision paper is to present the project "DICA-VE: Driving Information in a Connected and Autonomous Vehicle Environment: Impacts on Safety and Emissions", which aims to develop an integrated methodology to assess driving behavior volatility and develop warnings to reduce road conflicts and pollutants/noise emissions in a vehicle environment. A particular attention will be given to the interaction of motor vehicles with vulnerable road users (pedestrians and cyclists). The essence of assessing driving volatility aims the capture of the existence of strong accelerations and aggressive maneuvers. A fundamental understanding of instantaneous driving decisions (through a deep characterization of individual driver decision mechanisms, distinguishing normal from anomalous) is needed to develop a framework for optimizing these impacts. Thus, the research questions are: 1) Which strategies are adopted by each driver when he/she performs short-term driving decisions and how can these intentions be mapped, in a certain road network?; 2) How is driver's volatility affected by the proximity of other road users, namely pedestrians or cyclists?; 3) How can driving volatility information be integrated into a platform to alert road users about potential dangers in the road infrastructure and prevent the occurrence of crash situations?; 4) How can anomalous driving variability be reduced in autonomous cars, in order to prevent road crashes and have a performance with a minimum degree of emissions? This paper brings a literature review on this topic and an evaluation of methods that can be used to assess driving behavior patterns and their influence on road safety, pollutant and noise emissions.

Keywords: Driving volatility; Pollutant emissions; Safety; Noise

1. Introduction

Connected vehicles (CVs) are vehicles interacting with each other (V2V), roadside infrastructure (V2I, I2V) and beyond (V2X) via wireless communications [1]. While a number of studies have focused on investigating driving behavior, detailed data about driving performance has become available only recently [2].

Vehicle speeds and accelerations are key information to describe driving behaviors. Driving above the speed limit or above the recommended speed for a certain road situation is normally characterized as an aggressive behavior [3]. However, the speed choice depends partly on the roadway conditions, including surrounding traffic, obstacles, pavement and speed limits [4,5]. Researchers provide several acceleration cut-off points as the thresholds for identifying aggressive driving behaviors [6,7]. To assess variations in driving behaviors under different road contexts, varying acceleration thresholds, given different speeds for identifying anomalous driving behaviors were proposed [8,9]. These studies have given the idea of volatility as the extent of variations in driving, characterized by hard accelerations/braking, lane changes/turns, and unusually high speeds for roadway conditions. Identifying extreme driving behavior by using Safety Messages (SMs) and providing informative warning messages and control assists to drivers through V2X applications is still under development. SMs are messages exchanged between drivers [10], but they do not inform about their speed/lane change/turning decisions, since most of SMs describe normal driver behaviors. Thus, it is critical to identify anomalous driving behaviors and provide information to warn drivers through connected vehicle applications. One approach is trying to link the generation of warning messages to drivers' behavior. In some studies, the authors have initiated efforts to extract useful information from SMs to understand the drivers' behavior. For instance, a measure of driving performance in connected vehicles under different conditions of the network can be defined as “driving volatility” [8]. Other authors already studied trip-based volatility using high frequency connected vehicle data [9] and proposed some methods to identify anomalous behaviors from SMs [10]. Both demonstrated research potential for the generation of warnings/alerts for CVs informing drivers about the eminence of crashes. However, none of these studies focus on emissions reduction.

There are different ongoing research topics in the CVs field. Topics such as network robustness and information propagation efficiency [11-12] are still under investigation in order to establish a better V2V and V2I connection [11]. Also, there are a number of studies (not necessarily on CVs) trying to characterize an aggressive, driving style [10]; namely, risky driving behaviors have been found to be positively correlated with the likelihood of crashes or near crash events [13]. There is research related to CV systems that proposed mechanisms for warnings or alerts to drivers using CV applications and their effect on safety [14-16]. Although, positive effects of warning messages have been investigated, the way those warnings should be created is still under study.

Looking to vulnerable road users, the interaction between cyclists-motor vehicles is a clear research gap, because cyclists movements are very hard to predict (they are much less predictable than cars because it is easier for them to make sudden turns) [19]. Also regarding the interaction between motor vehicles and bicycles/pedestrians, several macroscale studies gather consensus that the vehicles' speed influences the risk and severity of the crash [20-21]. Other authors concluded that pedestrian has a higher risk than a cyclist does in the road environment, since drivers had more braking behavior in vehicle-cyclist than in vehicle-pedestrian interactions [22]. However, in none of these studies, the driving volatility and detailed maneuvers are analyzed microscopically.

Previous research suggests that driver's immediate decisions are often inconsistent and context-dependent, especially when the consequences are abstract (such as emissions hotspots). Even though the transportation literature is rich in studying driving behavior and ITS influence on safety and emissions [23,24], to the authors’ knowledge, real-time anticipatory driver behavior in a connected and automated vehicles road environment has been rarely used in risk identification, in order to reduce the probability of crashes as well as to mitigate local noise and pollutants emissions impacts. In addition, a microscopic analysis focused on the interaction between motor vehicles and vulnerable road users (pedestrians/cyclists) is not properly developed.

Thus, the main objective of this paper is to present the project “DICA-VE: Driving Information in a Connected and Autonomous Vehicle Environment: Impacts on Safety and Emissions” and to propose an integrated methodology to assess driving behavior volatility and develop warnings to reduce road conflicts and pollutants/noise emissions in a connected vehicle environment.

2. Methodology

A fundamental understanding of instantaneous driving decisions and distinguishing normal from anomalous driving patterns is required to develop a framework to generate early warnings and control assists due to extreme events. This research is composed by the following phases:

1. Acquisition of experimental data
2. Development of a real time Markov Decision Process (MDP)
3. Analysis of the effect of the presence of other road users in modifying driver decisions
4. Estimation of driving behavior deviation from normal to anomalous driving patterns
5. Estimation of safety, pollutant emissions and noise impacts

On the first phase, experimental data is being gathered. Participating vehicles are being equipped with Data Acquisition Systems; the datasets will contain vehicles instantaneous driving status, including position (altitude, latitude and longitude), motion (speed and acceleration), major components' status (accelerator level, use of cruise control), instantaneous driving contexts (namely to surrounding road users, evaluating the distance to them) and emissions. In addition, on-board emission measurements are being performed in motor vehicles using an integrated portable emissions monitoring system (iPEMS), the 3DATX parSYNC. This will allow the update of VSP emission factors. Finally, sound pressure levels will be collected with a sound level meter, in order to calibrate and validate the noise predictive models. Besides motor vehicles, the research team is collecting data also in bicycles (in order to address the interaction of motor vehicles with the vulnerable road users) [25].

Secondly, to predict micro behaviors, driver performance models of acceleration, deceleration and lane changing decisions will be estimated using Markov Decision Processes (MDP) [26, 27]. A key contribution of this research to develop a robust mathematical framework capable of estimating MDP parameters using statistically rigorous methods and microscopic data collected from road experiments. Surrounding traffic conditions, vehicles speed, level of service along the route, maneuvers variables will be taken into account.

Phase three will explore and model group behaviors, namely the interaction of different types of road users (drivers of motor vehicles, pedestrians and cyclists). For example, the propensity of a driver to speed up if other vehicle(s)/pedestrian(s)/bicycle(s) is(are) in his/her vicinity will be assessed. Next, driving patterns will be grouped and classified, from normal to anomalous.

On phase 5 a driving volatility indicator for measuring safety, noise and pollutants emissions thresholds of intended maneuvers will be defined, in different road environments. Several measures of driving volatility will be compiled and linked to probabilities of crashes occurrence as well as its influence on pollutants and noise hotspots. Thus, this will enable to obtain fuel consumption, pollutant emissions, noise emissions and crash risk analysis in the next phase. Here several computational models will be used, such as the VSP numerical methodology (for emissions), safety models (such as SSAM) and noise models (such as CNOSSOS-EU [28] and Quartieri et al. [29]).

Finally, the numerical methodology will be integrated and applied, in order to assess the detailed effect of driving volatility not only on greenhouse gases emissions targets, but the remaining local pollutants will not be forgotten, since they have a direct effect on human health. Also, the mitigation of imminent-crashes and noise levels will be assessed. Finally, the policy implications of proactive safety and pollutants/noise emissions management will be discussed.

2.1. Markov Decision Processes

MDP [25] provides the mathematical framework for modeling discrete decision problems. It includes a decision maker (the driver), state (defined by traffic conditions, level of service, current vehicles speed), actions (maneuvers, and variables such as acceleration, deceleration, lane change, etc.), the state transition probability matrix, and the transition reward matrix. The transition rewards are numerical measures of the utility associated with transitioning to a desired state, e.g., transitioning from a car-following state to a free flow state. It will be assumed that the driver selects the optimal action. The state transition probability is dependent on the vehicle dynamics. It is possible to distinguish between the effective maneuver performance and the intent to do so. The transition probability and the rewards are two counter-balancing factors: when the transition probability is high, even a small utility associated with lane change will cause the driver to initiate a lane change maneuver; if the probability of successful transition is very low (for example, in the state of low visibility), only drivers who associate an extreme utility to lane change will risk a maneuver [25]. Consistent daily driving habits lead to consistent utility measure estimates.

This consistency affords an opportunity for the control system to learn a driver's behavior by identifying MDP parameters through Inverse Reinforcement Learning (IRL). The sampling technique used will be one Markov chain Monte Carlo [26, 30] that generates a Markov chain. IRL process with its computational overhead will not be performed real-time, but the learning parameters will be periodically updated while the vehicle is stationary. Once the utility function is established, calculating optimal policy using state transition probabilities can be performed very efficiently and will be performed in real-time.

2.2. Emissions

Emission estimation is based on the concept of Vehicle Specific Power. The scope of analysis is focused on vehicular emissions for global (CO_2) and local (NO_X, CO, and HC) pollutants. VSP is computed from a second-by-second speed profile based on parameter values for a typical Light-Duty Vehicle (LDV) [31-34]. Equation 1 provides the generic VSP equation from a typical LDV:

$$VSP = v.\ [1.1\ a + 9.81\ (a.\tan\ (\sin\ (grade))) + 0.123] + 0.000302v^3 \tag{1}$$

where: VSP – vehicle specific power (kW/metric ton); v – Instantaneous speed on a second-by-second basis (m/s); a – acceleration-deceleration rate on a second-by-second basis (m/s^2); grade – road grade (slope). Each VSP bin refers to one of 14 modes. Each mode is defined by a range of VSP values that are associated with an emission factor for CO_2, CO, NO_X and HC concerning Gasoline Passenger Vehicles (GPV), Diesel Passenger Vehicles (DPV) and Light Duty Diesel Trucks (LDDT).

2.3. Safety

SSAM automates traffic conflict analysis by processing vehicle trajectories from a microscopic traffic model as VISSIM. After that, it records surrogate measures of road safety and determines whether an interaction between vehicles satisfies the condition to be considered a conflict [35, 36].

Time-to-collision (TTC) is used as a threshold to define whether a vehicles interaction is a conflict. This surrogate measure is defined as the minimum time-to-collision of two vehicles on a collision route. Minimum TTC and Post-Encroachment Time (PET) are used to assess the severity of a given conflict event while Deceleration Rate (DR), maximum speed (MaxS) and maximum relative speed difference (DeltaS) are indicators of the potential crash severity [36].

2.4. Noise

As for noise emission of the single vehicle, the CNOSSOS-EU model [28] suggests to estimate the source power level of the *i*-th vehicle, belonging the *m*-th category (light, medium, heavy duty and motorcycles), with v_m as the mean speed of the flow in the *m*-th category, as the log sum of the rolling noise $L_{WR,i,m}$ and the propulsion noise $L_{WP,i,m}$:

$$L_{W,i,m}(v_m) = 10\ \log\left(10^{L_{WR,i,m}(v_m)/10} + 10^{L_{WP,i,m}(v_m)/10}\right) \tag{2}$$

Rolling noise and propulsion noise are calculated according to the following formulas:

$$L_{WR,i,m} = A_{R,i,m} + B_{R,i,m} \cdot \log\left(\frac{v_m}{v_{rif}}\right) + \Delta L_{WR,i,m}(v_m) \tag{3}$$

$$L_{WP,i,m} = A_{P.i.m} + B_{P,i,m} \cdot \frac{(v_m - v_{ref})}{v_{ref}} + \Delta L_{WP,i,m}(v_m) \tag{4}$$

in which *A* and *B* are coefficients given in [28], ΔL are the corrections to both the noise contributions and v_{ref} is the reference speed (70 km/h).

The noise assessment of the entire traffic flow can be performed using a "semi-dynamical model" proposed by Quartieri et al. [29]. This choice is aimed at using a simple but effective model, that has been tested on different measured noise levels, in different conditions [37, 38].

The model is based on the assumption that the transits of vehicles contribute to the noise emission of the source "road traffic", influencing the total amount of noise measured at the receiver. The source power level is evaluated by means of field measurements fit. Considering the average speed of the traffic flow, each transit is assessed calculating the Sound Exposure Level (SEL) and, after summing on the number of vehicles, the total SEL is converted to the continuous equivalent level L_{eq}, measured in dBA:

$$L_{eq}^{1h} = 10\log(Q_L + n\, Q_P) + \alpha_L + \beta_L \log v - 20\log d - 46{,}563 \tag{5}$$

where L_{eq} is the continuous equivalent level (dBA), Q_L and Q_H are the hourly traffic volume respectively for light and heavy duty vehicles (vehicles per hour, vph), n is the acoustic equivalent (i.e. the number of light vehicles that approximately produce the same noise of a heavy vehicle), α = 53.6 (dBA) and β = 26.8 (dBA) according to [29], v is the average speed of the flow (km/h) and d is the distance between the road axis and the receiver (m). The traffic volume can be divided in light and heavy vehicles,

A comparison between the CNOSSOS-EU and the Quartieri et al. models will be performed, in order to compare the results with different approaches for single vehicle noise emission.

3. Conclusions and future work

The methodology to be developed under DICA-VE project will provide new and effective early warnings and control assists to change driving behaviors. The proposed activities will enable: 1) the production of warnings and assists to drivers in advance, based on anticipated maneuvers that might be potentially unsafe; 2) mapping the influence area of potential probability for incidents' occurrence and pollutants/noise emissions hotspots; 3) maneuver suggestions to drivers in the event of an incident. This will advance knowledge of anomalous driver behaviors that lead to undesirable outcomes and explore innovative ways to avoid them.

In line with EU2020 agenda for the implementation of sustainable cooperative traffic management systems, this research involves data capture and processing, algorithm development, impacts modeling, optimization and implementation, as well as implementing interdisciplinary actions. Departments of Transportation, private companies operating in intelligent transportation system, vehicle manufacturers and the research community will benefit from the research outcomes.

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