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Estimating reaction time in Adaptive Cruise Control systems

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Abstract— **Vehicle automation and cooperation is progressively being introduced in traffic networks. As a consequence research to assess its impacts is currently on-going. Adaptive Cruise Control (ACC) is one of the first automated functionalities available for privately owned vehicles. An experimental study has been conducted to investigate the key features of the ACC controller using Global Navigation Satellite System data. The first remarks based on the data focus on the controller's reaction time and desired time gap. Both parameters are essential in order to assess the influence of these technologies to safety and traffic flow. It is a common assumption that autonomous vehicles will have negligible reaction time and desired time gap comparable to that of a human driver. This paper presents an experimental study of an ACC-enabled vehicle on car following mode and a methodology for the estimation of the controller's reaction time that can be used as benchmark in other scenarios. The results show the reaction time to be around 1.1s and the time gap to be distinctly larger than that of a human driver. This poses concern on the impact of ACC on traffic flow when a significant number of vehicles will have such systems operating on-board.**

I. Introduction

In the next decades, the transport sector will undergo a deep transformation with the advent of Connected and Automated Vehicles (CAVs) [1]. Driver assistance technologies will evolve up to a point in which the complete dynamic driving task can be safely taken over by the vehicle, in every driving situation possible (i.e. the ultimate SAE level 5 full automation [2]). Furthermore, achieving a sustainable transport system becomes more and more challenging given the expected increases in passenger and freight transport (a growth by about 42% and 60% from 2010 to 2050, respectively), road transport being the main transport mode used in the EU [3].

Complete automation in driving will not arrive instantaneously and it is expected that there will be coexistence of manual, partial and fully autonomous vehicles for a long period. Embedding connectivity and automation to vehicles gives new unprecedented capabilities in comparison with the way we travel today [4]. On the other hand, it is difficult to estimate impacts related to potential increases in travel demand. Privacy and security challenges can emerge with the connectivity and coordination of vehicles [5]–[7].

It is important to see how the advanced automated functionalities will work in terms of safety, comfort and human driving standards. There are only few studies in the literature dealing with automated systems on real data. In simulation studies, the impact in the network, when favoring one parameter over the other, is very large and thus inappropriate model design can easily point to misleading conclusions.

One of the most important automated functionalities is the Adaptive Cruise Control (ACC), a system already available in the market. ACC can be enabled and disabled by the driver upon request and it can automatically accelerate or decelerate a vehicle with the goal to maintain a predefined time gap with a leading vehicle or to reach a desired velocity. ACC uses sensors such as LiDARs or cameras to detect and track the vehicle ahead (along with other moving or still objects) for measuring the actual distance and speed difference [8]. If a vehicle runs in front of the host vehicle at a slower speed, the throttle and braking system are controlled to maintain the inter-vehicle gap, set by the driver [9].

This work presents an experimental study of an ACC-enabled vehicle that follows another one and a methodology of estimating the reaction time of such systems that can be adopted in other scenarios. In this work, the experiments were conducted over a predefined track in the Joint Research Centre (JRC) in Ispra, Italy. The proposed methodology estimates the reaction time and the time gap of the ACC system based on real measurements obtained from Global Navigation Satellite System (GNSS) receivers using two vehicles in car following mode. In order to conclude on the reaction time of the system, this work correlates the acceleration of the follower with the inter-vehicle speed difference. Furthermore, the distribution of the time gap values during each lap is used to approximate the desired time gap of the ACC for that lap. A range of possible time gap values is derived and presented in the results section. Since ACC algorithms are not available by the industry, in this work we assume that the behavior between different manufacturers can be considered similar in terms of their impact on traffic flows over a network. The results from the present study show that contrary to prevalent opinion in the current literature, ACC has high reaction time values, close to human ones. Regarding ACC, which is able to look only one vehicle ahead, this conclusion, if it is verified in more controllers available in the market, can cause serious

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instability issues and can have a negative impact on the flow of the network.

II. LITERATURE REVIEW

When it comes to simulating technologies such as ACC, it is important to set up realistic parameter values and take into account proper safety thresholds. These parameters can determine the impact of traffic flows within a network. Few studies have been conducted using real data. Accurate models of the dynamic responses of ACC systems are needed to produce realistic predictions of their effects on highway capacity and traffic flow dynamics [10]. Simulation studies using ACC models conclude that setting the correct parameters is a difficult task. For example, it was noticed that the capacity increases with ACC penetration rate as long as the time gap setting is less than 1.10 s - 1.20 s. In cases where this value is higher, the capacity decreases with the penetration rate [11]. Other results show that smaller time delays and larger time gaps improve safety performance, but inappropriate parameter settings increase the collision risks and cause traffic disturbances [12]. The most common models for simulating ACC behavior used in the literature are the Improved Intelligent Driver Model (IIDM) [13] and the more recently proposed model by Shladover et al. [14]. Regarding indicative time gap values reported in the literature, manual vehicles have time gaps between 0.67 and 1.68 s, while ACC-equipped vehicles between 0.8 and 1.2 s.

In a study, which seems to point to the opposite direction than this work does, Jerath and Brennan [18] showed that the highway capacity drastically increases when the percentage of ACC-equipped vehicles approaches 100%, using the General Motors car following model.

Besides time gap, another parameter that it is currently overpassed in the various published simulation studies is the reaction time. In the simulation of manual driving, using for example the Gipps model [18], the reaction time parameter is described as the time from the moment that the leader acts to the moment that the follower reacts. In automated driving, this value is often assumed negligible, i.e. approximately zero.

While scanning the literature for prevalent values of reaction time in ACC controllers, it is apparent that this issue is not clear. In [10], [19], some of few studies with real data, the authors admit that there is a delay in ACC but they don't provide any quantifiable result. The possible presence of significant delays in ACC were mentioned for the first time in [20]. The authors highlighted the danger of instability in cases of ACC platoons with reaction times that are against both safety and comfort of the passengers. In [14], [21]–[23], the authors mentioned delays in the order of 0.4-0.5 s in ACC. In some older studies, the ACC response time was considered of the order of 0.1–0.2 s and therefore negligible when compared with the human reaction time of about 1 s [27], [28].

III. EXPERIMENTAL SETUP DATA ACQUISITION AND PROCESSING

The results presented in this work refer to experiments that took place in the JRC Ispra in October 2017. Two vehicles were equipped with two commercial multi-constellation GNSS receivers able to collected GNSS data with a 10 Hz measurement rate. The receivers on the two vehicles were of the same type/model and configured to collected signals from both GPS and Galileo, the European GNSS. In this way, the receivers were able to process up to 16 satellite signals. This condition is considered very positively as it enables good receiver performance (a minimum of 4 satellite signals is required for positioning using a single constellation). The average horizontal accuracy reported by the receivers was less than 50 cm. GNSS active antennas were mounted on the roof of the cars in order to ensure maximum satellite visibility and avoid signal attenuations from the body of the vehicles. The locations of the antennas with respect to the body of the vehicles were carefully surveyed. In particular, the lever arms between the antenna locations and the back and front bumpers of the vehicles were carefully determined. The lever arms are the vectors between the antenna location and the back/front bumpers and are required to obtain the positions of the bumpers from the position estimated by the GNSS receiver. This principle is illustrated in Fig. 1 that shows the experimental setup adopted for estimating the vehicles position and dynamics.

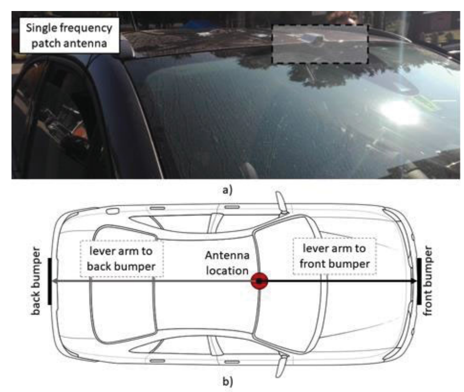

Figure 1. Experimental setup adopted for measuring the vehicles position and dynamics. a) Location of one of the GNSS antennas used for the data collection. b) Schematic representation of the antenna location and of the lever arms to the front and back bumpers of the car.

The GNSS receivers mounted on the two vehicles were used to collect the location of the two vehicles. In particular, at each time instant, t_i , the geographic coordinates (latitude, longitude and height) of the vehicles were recorded. These coordinates were then transformed into a local North, East and Up (ENU) Cartesian reference frame. The lever arms determined at the beginning of the experiment were used to determine the location of the front and back bumpers of the two vehicles in the ENU frame. The locations of the bumpers of the two vehicles were then used to compute the distance between leading and following vehicles, $dist_{l-f}(t_i)$. In particular, $dist_{l-f}(t_i)$ is obtained as

$$d_{l-f}(t_i) = \sqrt{\left(N_f(t_i) - N_l(t_i)\right)^2 + \left(E_f(t_i) - E_l(t_i)\right)^2 + \left(U_f(t_i) - U_l(t_i)\right)^2}$$

where (N_f, E_f, U_f) are the coordinates of the following car and (N_l, E_l, U_l) are the coordinates of the leading vehicle. GNSS data were also used to estimate the speeds and accelerations of the two vehicles.

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The experiments were conducted under clear-sky conditions and the position and velocity information, as internally determined by the receivers were directly used. In particular, the data collected with the GNSS receivers were considered of sufficient quality for the analysis performed in the following.

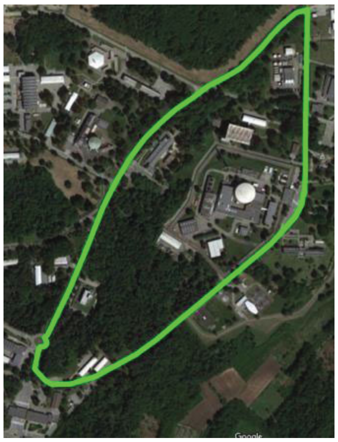

Figure 2. Path followed by the vehicles inside the JRC-Ispra site.

In the experiments conducted, the vehicles were moving on a predefined route about 1.15km long inside the JRC under normal traffic conditions. The track performed for the experiments is illustrated in Fig. 2 this track was repeated several times and several laps were performed. A summary of the laps performed is provided in Table I.

TABLE I. SUMMARY OF THE TESTS CONDUCTED.

Laps	**Data specifications**		
	Driver	***Desired Speed km/h***	***Duration***
21	ACC	[40,50,60,70]	24.1km of driving in 83.6 mins
4	Manual	-	4.6 km of driving in 14 mins

It should be noted that the specifications of the experiments above are only indicative in the sense that the car following measurements were performed on an active road network with other vehicles in the loop. Moreover, it is necessary to take into account the presence of measurement errors that can arise from the GNSS solutions. Finally, it was observed that in certain turns the ACC was losing the leader from its sight, accelerating sharply to reach the desired speed and therefore manual intervention was needed to avoid having an accident. This problem is common for roundabout intersections [29] and car manufacturers are still working to a reliable solution for this issue [30]. Although no filtering was applied in pre-processing, i.e. measurements were not removed, the large amount of data and the consistency of the results allow one to consider the findings obtained reliable.

IV. METHODOLOGY

The aim of the proposed methodology is to provide insights regarding the reaction time of an ACC system that currently exists in the market, while the ACC-enabled vehicle is in car following mode. Furthermore, the authors intend to have this method as a benchmark between different ACC controllers with variable characteristics. For the needs of the present study, it is considered that in terms of impact assessment on traffic flows ACC controllers available in the market have similar performance. The reaction time in car following simulation is considered as the time needed for the driver of the following vehicle to react to an action of the leader driver. The ACC system, as clearly indicated in the manual, checks the speed difference between the follower and the leader, as well as their distance. The goal is to maintain a constant time gap.

We consider reaction time as the time needed for the ACC controller to react on an action of the leading vehicle, while initially they were both in a stable state. Two vehicles are considered to be in a stable state when their acceleration is zero and both have roughly the same speeds. The possible actions that can be done by the leading vehicle are two, either acceleration or deceleration. The vehicle's controller obtain information about its speed, the speed of the leader vehicle and their relative distance. During the data analysis, we have observed a strong linear correlation between the relative speed of the two vehicles and the acceleration chosen by the controller. This correlation is visible only when the reaction time lag is taken into account. This lagging factor can be justified because of the time needed to process the data and act.

So, in order to estimate the reaction of the ACC controller, the follower's acceleration, $acc(t_i)$, and the difference in the speed between leader and follower, $spdiff(t_i)$, are compared for each measurement, i. Next, $acc(t_i)$ is shifted for an interval between 0.1 and 4 s with a step of 0.1 s. For each shift, the Pearsons's correlation coefficient, r, is computed. The shift value that corresponds to the highest r can be considered as the estimated reaction time of the following vehicle. For each shifted time series, $acc(t_i - s)$ with $s \in \{0, 0.1, \ldots, 4\}$, the Pearson's correlation coefficient can be computed as

$$r(s) = \frac{\sum_{i=1}^{n} (acc(t_i - s) - \overline{acc}) \times (spdiff(t_i) - \overline{spdiff})}{\sqrt{\sum_{i=1}^{n} (acc(t_i - s) - \overline{acc})^2} \times \sqrt{\sum_{i=1}^{n} (spdiff(t_i) - \overline{spdiff})^2}}$$ where

$\overline{acc}$ and $\overline{spdiff}$ are the sample means of the time series used for the computation of $r(s)$.

Finally, the reaction time can be estimated by finding the maximum of the derived set of coefficients:

$$rt_{est} = \max(\{r(s) : s = 0, 0.1, \ldots, 4\})$$

An illustration of the above-described procedure is provided in Fig. 3. The upper figure shows the vehicles' speed difference synced (action) with the acceleration of the follower (reaction). A clear lag can be observed between these two time series. The bottom part of the figure is obtained after shifting the two time series in order to maximize their correlation and consequently estimate the reaction time.

The time gap is another parameter used in microsimulation for which, to the authors' best knowledge, the available literature about ACC controllers is quite limited. In this work, we define the time gap according to the following formula:

$$tg_{t_i} = \frac{dist_{l-f}(t_i)}{s_f(t_i)}, \forall t_i \in \{0, 0.1 \ldots, T\},$$

where T is the duration in seconds of one lap of the driving experiment. t_i is varied with a 0.1 s step, the inverse of the measurement sampling frequency (10 Hz). $dist_{l-f}(t_i)$ is the inter-vehicle distance defined above. The speed of the follower is $s_f(t_i)$. In order to approximate the time gap used by the vehicle over a lap, we created the corresponding time gap distribution using histograms. Time gaps with higher occurrences are the most likely and can be considered as the desired time gap value set by the driver. In the end, after the extraction of the time gap distribution, this work keeps the median value as an approximation of the desired time gap value.

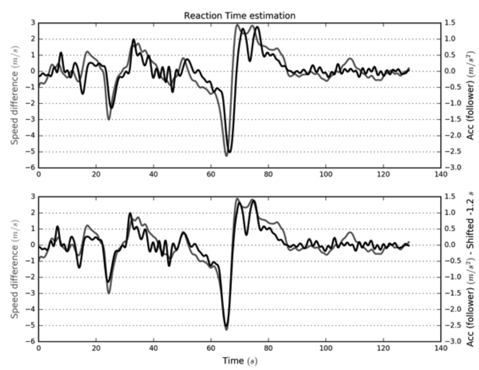

Figure 3. Estimation of reaction time based on maximizing time series correlation. Chart on top refers to the synchonized time series of the speed difference (light gray line) and the acceleration imposed by the ACC system (black line). Chart below refers to the same time series after shifting the acceleration profile by the estimated reaction time.

V. RESULTS

In this section, the experimental results obtained with the methodology described above are analyzed. Both vehicles drove, in total, 28.7 km, 24.1 of which using the ACC controller and 4.6 in manual driving conditions. The leading vehicle was driving in manual mode. The length of a single lap is roughly 1.15 km and, in total, the results refer to 25 laps. The speed limit in the track is 50 km/h and therefore the desired speed in the ACC controller took values between 40 km/h and 70 km/h.

The results obtained according to the methodology described above are reported in Fig. 4, as a function of the lap and of the driving mode, ACC or manual. In the figure there are three columns, the first one provides the estimated reaction time based on the Pearson's coefficient, the second one shows the maximum level of correlation found between the acceleration of the follower and the inter-vehicle speed difference and the third one is the estimated time gap. The bullets in the figure are colored based on the correlation coefficient found, that is, the darker ones indicate strong correlation (values close to one) while the lighter ones point to less reliable estimation (values far from one approaching zero). It is interesting to notice that the ranges of the obtained values are small, which indicates consistency. As expected, the correlation in the manual driven laps is lower as the goal of keeping the time gap constant is not present in these laps. The estimated values for the reaction time and the time gap observed in our tests can be summarized as follows:

Reaction time: 0.9 - 1.3 s for ACC mode and 1.4 - 1.5 s for the manual driving.

Time gap: 1.4 - 2.2 s for ACC mode and 0.8 - 1.3 s for the manual driving.

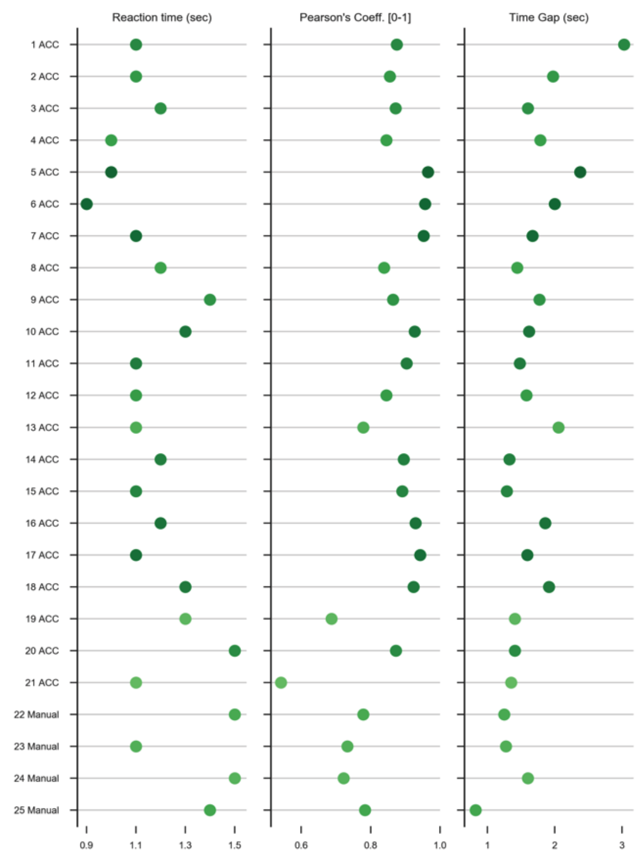

Figure 4. Estimated reaction time and time gaps per lap and per driving mode.

A. Driving with ACC

In almost all results, there is a high correlation between the follower's acceleration and the speed difference time series, validating the initial assumption. The reaction time has been found in the range between 0.9 and 1.3 s. This is in contrast with the prevailing opinion in the literature that the reaction time of the ACC can be considered negligible. Based on this misconception, the reaction time is not taken into consideration in the vast majority of the simulation studies and in the models used to simulate the ACC logic (e.g. IDM and a more recently proposed by Shladover et al [14]).

An illustration with the lack of reaction time in existing ACC models and the comparison with real data is shown in Fig. 5. The aforementioned Shladover model was used to simulate the car following behavior observed by the vehicle. While it can be appreciated that the model closely resembles the observed trajectory, it is always reacting faster than the real vehicle, hence the modeling error can be significant in more complex or critical circumstances. Of course the results found in this work need to be validated by further studies with ACC controllers from other vehicles. Still, the evidence provided here demonstrate that the impact of ACC or other autonomous systems on traffic flow needs careful investigation.

B. *Manual driving*

Results referring to manual driving are presented in this study as a complementary preliminary analysis. It is noted that the human driver's behavior is not imposed by specifications such as retaining the same relative speed or keeping a constant time gap. Thus, it is expected (and observed in the experimental results) that the corresponding correlation of the time series for the manually driven laps is significantly lower than the one observed in ACC mode. The reaction time of a human driver is, as anticipated, bigger than the one from the ACC controller. Furthermore, the time gap found under manual driving is smaller than the one detected for the ACC. According to this, it can be concluded that ACC is designed to favor safety and comfort over agility, with a potentially significant impact on traffic flow.

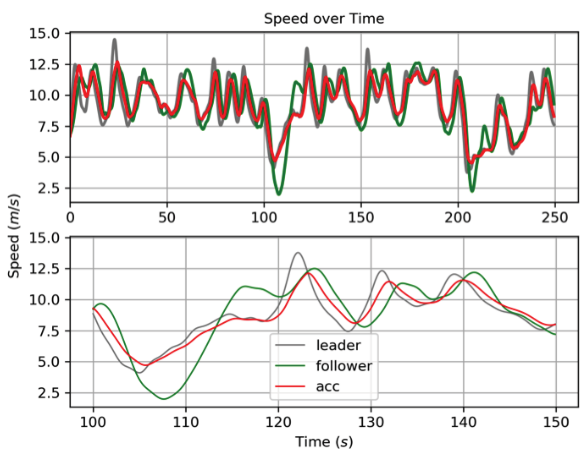

Figure 5. Speed over time for the leading vehicle, the following vehicles and an ACC model with no reaction time (a) one lap, (b) zoomed to part 100-150 s.

VI. CONCLUSION

The present paper focuses on estimating the reaction time of an ACC controller when it is under car following conditions. Although the behavior of currently available controllers in the market cannot be considered uniform, their impact in terms of traffic flows is expected to be similar. Since the ACC algorithms are not available by the industry, a methodology is proposed as a benchmark tool for expanding the current study to larger number of ACC controllers. To this aim, an experimental campaign was carried out in the JRC Ispra site in Italy, with two vehicles following each other. GNSS location data were processed to obtain relative distance and speed information. This information was used to estimate the reaction time of the following vehicle either for the ACC controller or for the human driver. The time gap was also analyzed.

Results show that the values of the reaction time currently considered in the literature and used for simulation purposes are too low in comparison with real measurements. Regarding the time gap, the values found in the experiments are slightly higher than the ones reported in the literature. The authors consider the results very important especially in microsimulation studies where an increase of the reaction time and/or the time gap can severely affect the conditions of the network, reducing the maximum capacity and generating more congestion. Consequently, these parameters might affect energy consumption and emissions over the area.

The main findings of the present work can be summarized as follows:

- ACC reaction times found close to the ones of humans.
- ACC car following models for microsimulation in the literature ignore or use low values for defining the reaction time of the vehicles.
- Time gap values found on real driving conditions are considered higher than the values found in the literature.

The present work is based on a study on an ACC system available in the market, but results cannot be generalized to all ACC systems. It is worth noting that the results are related to current in-vehicle technologies for models designed more on the basis of comfort than on the basis of facilitating traffic flows. This is something that needs to change over time with the anticipated automated vehicles and technological evolution of sensors and connectivity. Future work should be done on more controllers in order to extend this campaign and further support the validity of the conclusions presented here.

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