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Abstract

This paper investigates the observable response times of commercial cruise control systems. The behavioral comparison is performed based on empirical observations from three well-known experimental campaigns in the literature. In recent years, apart from the already commercially available Adaptive Cruise Control (ACC), an upcoming system called Cooperative Adaptive Cruise Control (CACC) has been developed to control the speed of vehicles. The goal of this work is to compare the behavior of these systems on the basis of response time, that is the delay from the moment of a stimulus until the reaction of the controller. Observations from two datasets with ACC and CACC experiments, the OpenACC dataset, developed by the European Commission and the CARMA dataset developed by the U.S. Department of Transporation, were considered. Three state-of-the-art techniques were implemented to provide quantitative results for the vehicles' response times. The benefits and downsides of each technique are discussed as well. The results show that ACC does not exhibit a significant improvement compared to human drivers, yet it can be concluded that the additional vehicle-to-vehicle communication incorporated in the CACC system allows a significantly lower response time.

Keywords

Automated Systems, Vehicle-Platooning, Response time, Adaptive Cruise Control, Cooperative Adaptive Cruise Control, Experimental Campaigns, Empirical Observations, Reaction Time

1 Introduction

In recent years, more and more commercially available vehicle models are equipped with Automated Driver Assistance Systems that support the driver by taking over particular driving tasks and enhance safety standards. The ongoing evolution towards full automation and vehicle connectivity will effect the characteristics of road transportation substantially (European Commission. Joint Research Centre, 2019). Not only the road safety, but also the road capacity and the vehicle travel times within a network are limited due to human driving behavior. Automated systems appear with a promise to eliminate the lack of reliability human drivers show and aim at making road transportation safer, faster and more comfortable. However, literature studies show that such positive impacts should not be taken for granted.

A system that has been on the market for over 25 years is the Adaptive Cruise Control (ACC). ACC controls the longitudinal movement of a vehicle (Driel, 2007). ACC either holds a particular speed preset or, different from conventional cruise control, adapts the ego vehicles speed if there is a slower vehicle ahead. The next step after the development of ACC is Cooperative Adaptive Cruise Control (CACC). CACC is based on the same functionality as ACC, but additionally, uses wireless communication between vehicles (V2V-communication) or between the vehicle and traffic infrastructure (V2I-communication) (Milanés *et al.*, 2014). An application within the field of vehicle automation is to establish car-platoons, which consist of several vehicles following each other in the same lane. Advanced automated systems such as CACC make it possible to couple the individual vehicles within the platoon and therefore achieve a more refined driving behavior. Hereby, the development of automated systems will enhance road capacity and reduce travel times (He *et al.*, 2019).

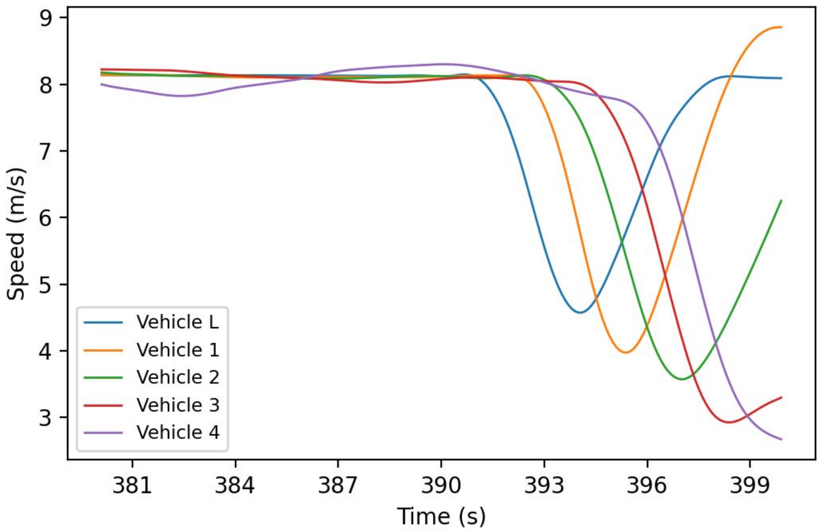
The response time (or reaction time) for vehicle drivers is a time-related property that has a physical meaning and resembles the delay between a stimulus and the response of the driver or system. This property is used in microsimulation modeling as well, and its values are directly related to the observed traffic flow. The estimation of the response time in real-world observations is a challenging task, mainly due to complexity of the controller's operation and the noise in measurements. The estimated response time from real-world is named as observable response time and it is different than the theoretical response time that the system could have under ideal conditions. For human drivers, it has been found that the reaction time (including perception, decision, and action) is about 1.2 s (with a standard deviation of 0.3 s), see Lanaud *et al.* (2021). For ACC systems, the corresponding response time has been found with similar values and it is not, by any means, instantaneous, i.e. below 0.4s, under normal driving conditions, see Makridis *et al.* (2020); Li *et al.* (2021). Regarding CACC, only preliminary findings exist in the literature and this is a gap that the present paper aims to fill. The present paper aims to systematically study the response time of ACC and CACC system in different datasets and with different methodological approaches. The goal is to provide results that are holistic (for both technologies), independent of the particularities of each dataset and independent of the benefits and downsides of each theoretical approach. Three state of the art approaches described in literature to estimate the response time, proposed in Makridis *et al.* (2020), Lanaud *et al.* (2021) and Li *et al.* (2021), have been implemented and applied on real-world observations. The three experimental campaigns used to provide quantitative estimates of this property can be found in Tiernan *et al.* (2017), Tiernan *et al.* (2019), and Makridis *et al.* (2021).

2 Discussion on different methods for response time analysis

The response time corresponds to the temporal delay a vehicle within the platoon shows when reacting to a change in speed performed by a preceding vehicle. The observable response time that can be estimated from the data consists of several factors. It does not only include the controller's physical limit but also the delay in communication with the subsystem and eventually the response strategy implemented by the manufacturer (Makridis *et al.*, 2020). The balance between a fast reaction time and a comfortable driving experience must be found. Short response times would lead to frequent speed adjustments and therefore result in uncomfortable acceleration and braking behavior. Long response times, on the other hand, are a potential safety risk, when a preceding vehicle applies hard braking.

In this work, the response time is estimated for the automated systems ACC and CACC. The experiments were designed with longer periods where the platoon drives at a stable speed (also called *equilibrium speed*) followed by an acceleration or deceleration performed by the leading vehicle. The following vehicles' controller adapts its speed as well, since it tries to hold a constant time-gap. After this so called perturbation, the platoon settles again either on the same or on a new equilibrium speed. Slices of the data around these perturbation events, between 30 and 70 seconds long, are used to estimate the observable response time within all the three estimation methods. Figure 1 shows exemplarily a perturbation event from the *ZalaZone* campaign with ACC vehicles, where *Vehicle L* is the leading vehicle and *Vehicle 1 - 4* are the following vehicles. It is obvious from the plot that there is a certain delay for the reaction of each following vehicle. Makridis *et al.* (2020) mention that the response time for acceleration perturbations is similar to the response time for deceleration perturbations. Therefore, it was not to be seen necessary to differentiate between the acceleration and deceleration events when estimating the reaction.

Figure 1: The platoon's speed profiles from the ZalaZone campaign during a perturbation imposed by the leading vehicle.



Three different approaches described in literature to estimate the response time have been implemented and applied on the data. The first method proposed in Makridis *et al.* (2020) (*Ma*) uses cross-correlation to determine the time delay of two signals. The second method proposed by Lanaud *et al.* (2021) (*La*) and the third method by Li *et al.* (2021) (*Li*) determine the time instants a vehicle starts its perturbation. In these cases, the response time corresponds to the difference between the time instants of two successive vehicles. In the subsections below, the three methods and their implementation will be discussed and presented in detail.

2.1 Cross-Correlation Response Time Method

This method proposed in Makridis *et al.* (2020) uses the cross-correlation of two signals to identify the time lag between the signals. Since the speed difference between two successive vehicles is the decisive factor for the controller's reaction (acceleration), the speed difference $\triangle v_{l-v,t}$ is considered as the first signal. The second signal is the acceleration of the follower $a_{f,t}$. To begin with, the cross-covariance function $\sigma_{\triangle v,a_f}(T)$ between the two signal is computed (Equation 1). Since the acceleration signal is shifted over the speed difference signal, a time delay T is applied to the acceleration signal. In the cross-covariance function, $\mu_{\triangle v}$ and μ_a describe the means of each signal and N is the number of measurements (length of the time series in seconds multiplied with the frequency, e.g., 10 Hz).

$$\sigma_{\triangle v,a_f}(T) = \frac{1}{N-1}\sum_{t=1}^{N}(\triangle v_{l-f,t} - \mu_{\triangle v})(a_{f,t-T} - \mu_a) \tag{1}$$

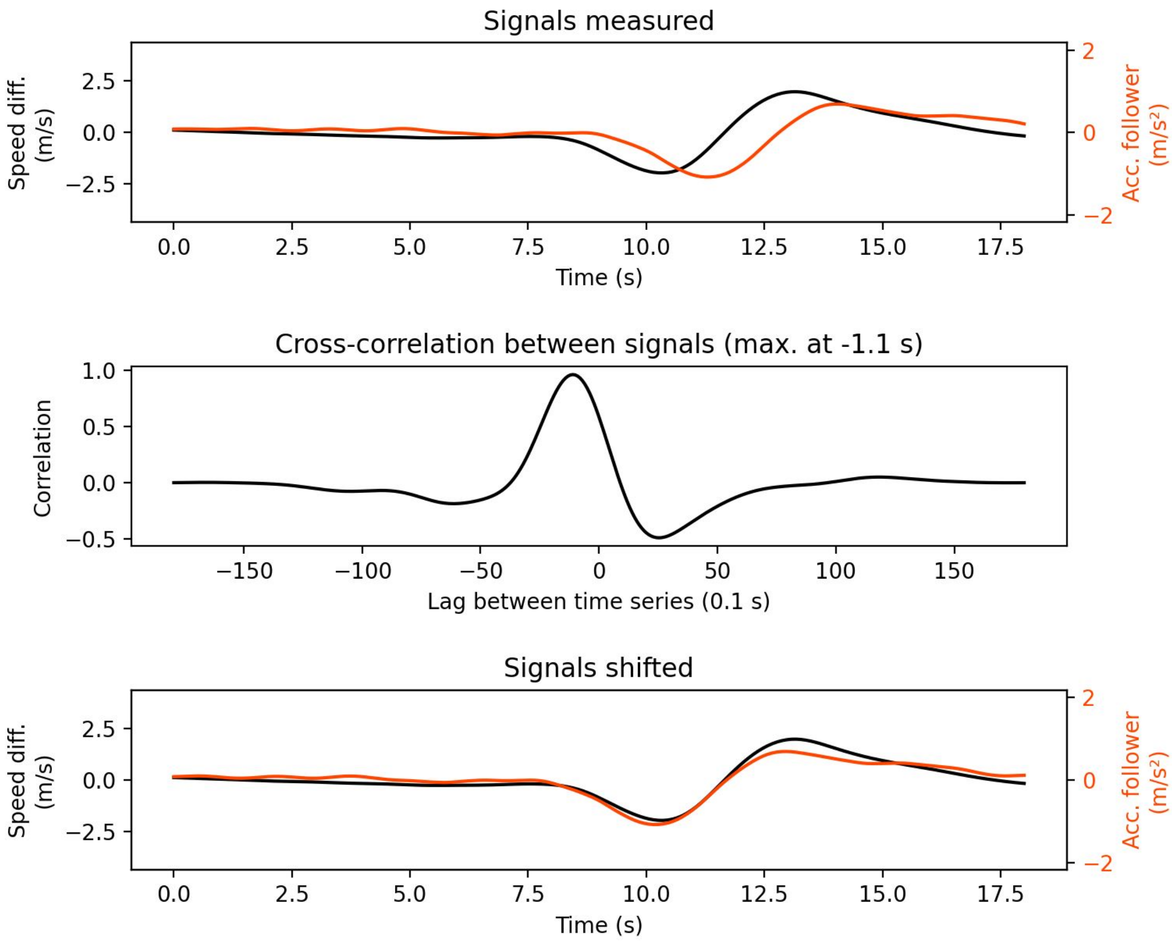
To compute the cross-correlation from the cross-covariance function, a normalization has to be performed. The cross-correlation $r_{\triangle v,a_f}(T)$ corresponds to the cross-covariance divided by the square root of the product of the variances of both signals ($\sigma^2_{\triangle v}$ and $\sigma^2_{a_f}$) (Equation 2). Finally, the delay where the cross-correlation is at maximum (τ_{delay}) can be considered as the estimated response time (Equation 3).

$$r_{\triangle v,a_f}(T) = \frac{\sigma_{\triangle v,a_f}(T)}{\sqrt{\sigma^2_{\triangle v}\sigma^2_{a_f}}} \tag{2}$$

$$\tau_{\text{delay}} = \text{argmax}(r_{\triangle v,a_f}(T)) \tag{3}$$

Figure 2 shows the actual speed difference and acceleration in the first subplot. The second subplot shows the cross-correlation function, where the estimated response time corresponds to the time delay at the maximum of this function. In the third subplot, the acceleration is shifted by this delay. One can clearly see that both signals match relatively well if the y-axis is scaled with the ratio of the standard deviations from the signals. Additionally, the value of the correlation coefficient provided by this method is a measure for the certainty of the estimation. Events with a coefficient lower than 0.95 have been excluded from the results. Moreover, the method is on the one hand robust with respect to noisy measurements, because it considers the whole slice of data in its correlation. On the other hand, the method reflects the average response time over the whole signal length, whereas the two methods following below focus on the response time directly at the beginning of the perturbation.

Figure 2: Cross-correlation of the speed difference (between two successive vehicles and the acceleration of the follower) to estimate the observable response time.



2.2 Acceleration Threshold Response Time Method

The method presented in Lanaud *et al.* (2021) determines the speed change instant, where a vehicle absolves a designated acceleration after driving at a stable speed. The difference between the speed change instants of two successive vehicles can be considered as the response time. The procedure for determining the speed change instants works as follows:

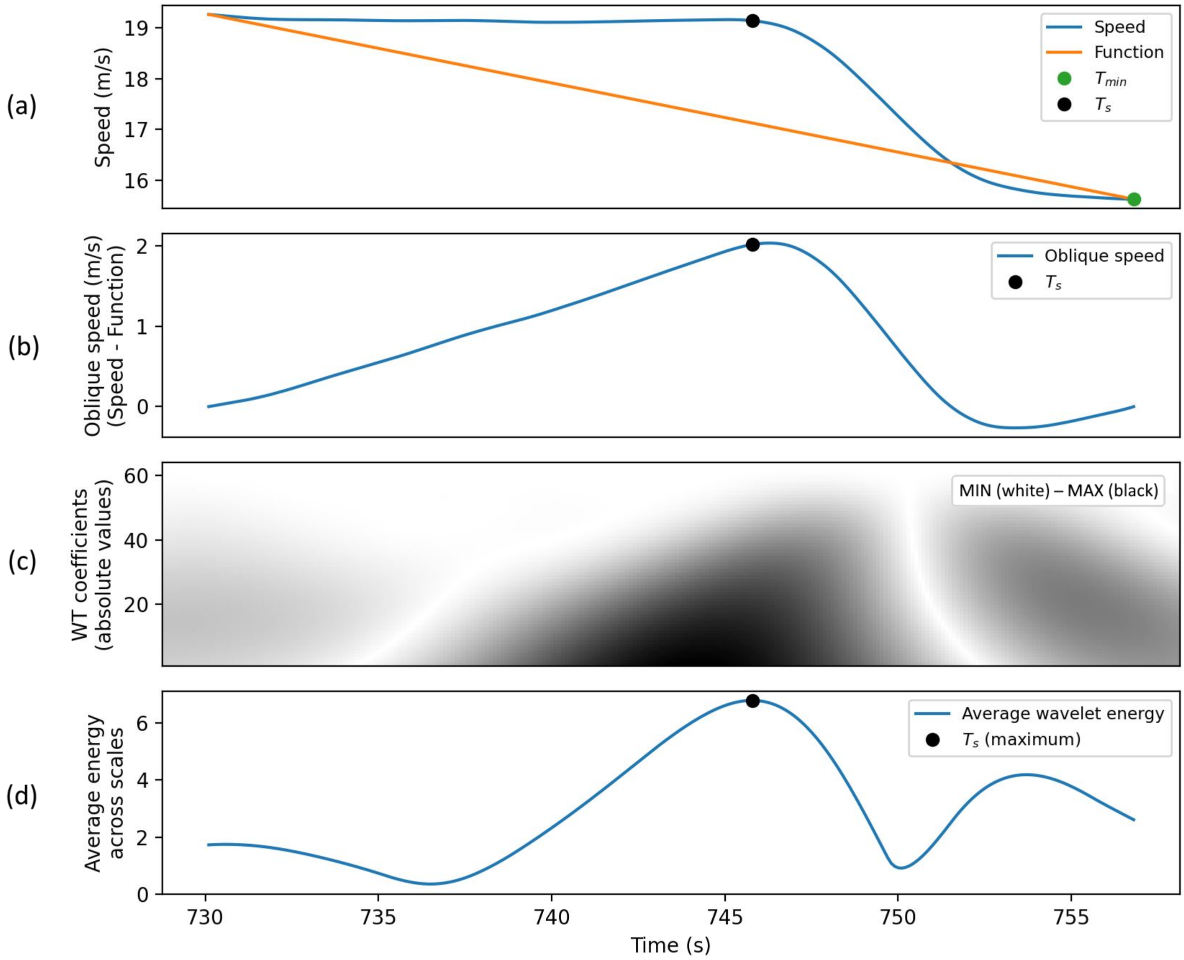
At the beginning, the rolling standard deviation of the vehicle's speed is calculated for a window of one second. Then, the gradient of the standard deviation is computed for each time step. Finally, the total variance over the whole data is calculated as the standard deviation of the gradient. To identify a speed change instant, the gradient, which reflects the acceleration, must stay below the total variance for a certain set time. Afterwards, the gradient has to exceed the threshold given by the total variance for a shorter period of time. Only if both conditions are met when iterating through the time series, a speed change is detected and the corresponding time stamp is saved. There are some parameters that may be adjusted so that the method fits to the data. The time periods, for instance, in which the vehicle's acceleration needs to be below the threshold or in which it needs to exceed the threshold can be changed. Furthermore, a factor applied to the total variance threshold allows to tune the sensitivity of the method.

It can be concluded that the method proposed by Lanaud *et al.* (2021) works well on the CARMA2 data, for which this method was originally designed. Yet when applying it to data from OpenACC dataset, the parameters mentioned above need to be adjusted for the method to work. The ACC vehicles are less stable around an equilibrium speed and the acceleration is not as strong compared to the CACC vehicles from the CARMA2 campaign. The detected response times have a high variation and they often prove as unreliable.

2.3 Oblique Speed and Wavelet Transform Response Time Method

This method proposed by Li *et al.* (2021) tries to detect the point in time where the acceleration or deceleration starts. It can be achieved by calculating the oblique speed profile and consequently by applying the wavelet transformation. To calculate the oblique speed, the speed profile of the whole perturbation is cropped to the moment, when the perturbation magnitude is highest. The next step in this procedure is computing a linear function from the speed at the beginning of the speed profile to the speed at the end of the now cropped slice of data.

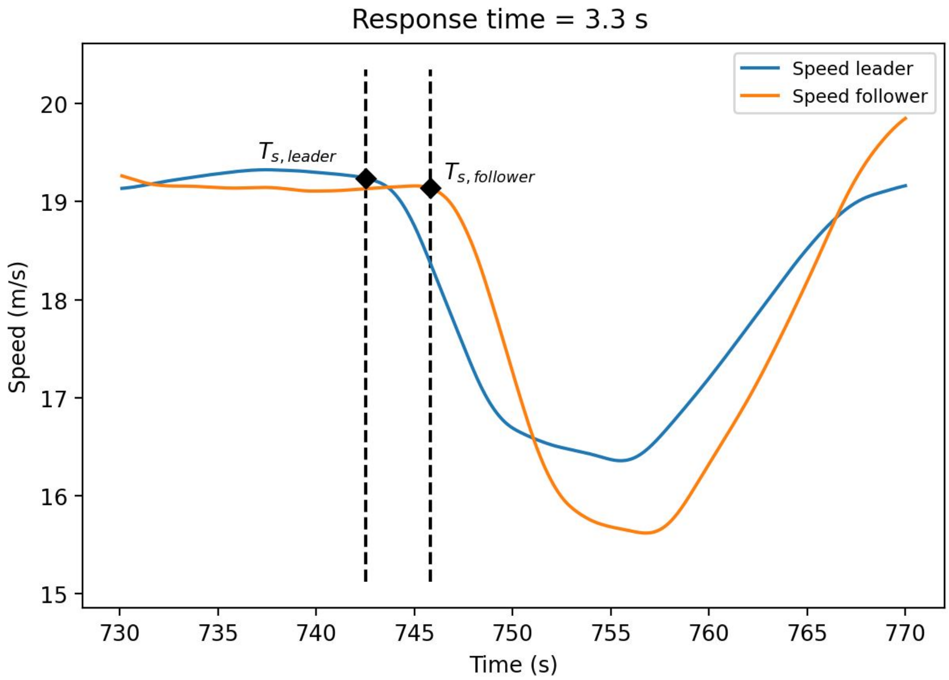
Figure 3: Speed (a), oblique speed (b), wavelet transform coefficients (c), and average wavelet energy (d) to identify the beginning of a perturbation.



The first subplot (a) of Figure 3 depicts the original speed profile of a vehicle and the linear function passing through the speed at the beginning to the speed at the end of the slice. The oblique speed is calculated by subtracting the linear function from the original speed profile. As shown in the second subplot (b) of Figure 3, the beginning of the perturbation is thereby emphasized, which will lead to a better recognition in the now following wavelet transformation.

The application of the wavelet transform to vehicles' speed profiles was originally presented by Zheng *et al.* (2011) to identify the location of a bottleneck. A so-called *Mexican hat* wavelet is applied to the oblique speed, with wavelet widths (*scales*) between 1 and 64. At the maximum value of the average wavelet energy across all 64 scales, the starting point of the perturbation is detected. The wavelet energy for the range of wavelet widths is presented in the third subplot (c). The fourth subplot (d) shows the absolute average energy across all these scales. Figure 4 shows the detected points on the speed profile of the leading and the following vehicle.

Figure 4: Detected perturbation starting points for a leading and following vehicle.



By reflecting the applicability of the method, it becomes clear that the detected point depends on the length of the time series data and the perturbation magnitude. On the one hand, including a longer period of the equilibrium speed before the perturbation occurs leads to a more flattened oblique speed and the acceleration or deceleration point is detected early. On the other hand, a high perturbation magnitude does make the oblique speed steeper and the detected point tends to be later. In case the following vehicle shows overshooting behavior, its oblique speed is steeper than the oblique speed of the leading vehicle and the maximum average wavelet energy turns out to be slightly later. Due to the delayed detection of perturbations with higher magnitudes for vehicles that are string unstable, the method is biased towards longer response times. Since the ACC vehicles with a small headway setting from the experiments used in this work are string unstable, the method results in higher reaction times for these vehicles.

3 Results

In this section, the results of the response time estimation with the three methods are presented and discussed in greater details. Firstly, the response times over all methods are reported and secondly, the differences between the methods are discussed. The response time for the vehicles in the AstaZero ACC platoon is estimated to be around 1.3 to 2.5 seconds. Furthermore, the response times observed for the ZalaZone ACC platoon are roughly between 0.5 and 2 seconds, and they are slightly increased for longer headway settings. The CARMA2 CACC platoon features by far the smallest response times with values between 0 and 1 second.

The difference of the estimated values between methods apparently results from the various functioning of the methods. Due to the opportunity of filtering the response times for their cross-correlation coefficient in the method from Makridis *et al.* (2020), the estimated values show less variation than the estimated values from the other methods. A high cross-correlation coefficient indicates good matching between the series and therefore a high estimation quality. However, the methods from Lanaud *et al.* (2021) and Li *et al.* (2021) do not provide such a key indicator. One has to examine the detected response times closely to ensure that the methods work properly. Another interesting difference is that these two methods result on average in slightly higher response times than the cross-correlation method from Makridis *et al.* (2020). Since they detect individual points in the speed data, they are very sensitive to the vehicles' behavior at the beginning of a perturbation. Especially the acceleration and deceleration sharpness effect the response time within the method from Lanaud *et al.* (2021). A less sharp reaction of a following vehicle leads to a delayed detection and therefore to higher response times. The method from Li *et al.* (2021) is influenced in particular by the perturbation magnitude of the follower. Following vehicles that dampen the perturbation, as it is the case within the CARMA2 platoon, have a smaller magnitude than the leading vehicle. The speed transition is detected earlier, which results in a lower response time. In the case of string instability, the opposite happens and the detected response time becomes larger.

In summary, all three methods exhibit the same evolution for CACC vehicles towards remarkably lower response times. The method proposed by Makridis *et al.* (2020) can be considered as the most robust approach to estimate the response time from the methods implemented in this work.

4 Conclusion

It was the goal of this work to achieve a better understanding of the behavior of advanced automated systems and more particularly the response time capabilities of systems that are commercially available (or will be soon) and are already considered the predecessors of autonomous vehicles. Car-platoon data from empirical observations of independent vehicle platooning experiments have been used to provide quantitative results on vehicles' response times. The two datasets used were the OpenACC dataset, developed by the European Commission and the CARMA2 dataset developed by the U.S. Department of Transportation. Three different techniques for the estimation of a vehicle's response time were implemented. The analysis has led to revealing results. Whereas the ACC response time is similar to the human driver's reaction, the CACC vehicles' response time is significantly shorter. More specifically, the response times for ACC have been observed to be in the range between 1.3 and 2.5 seconds. Furthermore, the response times for the CACC vehicles in the CARMA2 platooning campaign have been estimated between 0.1 and 0.5 seconds, that are impressively low values. Research done on the facets of response time in automated assistance systems show prospective results and further investigations will particularly focus on such effect on traffic flow.

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