Customer oriented vehicle dynamics assessment for autonomous driving in highway

Customer Oriented Vehicle Dynamics Assessment for Autonomous Driving in Highway

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Abstract

Autonomous Driving is one of the main subjects of academic research and one important trend in the automotive industry. With the advent of self-driving vehicles, the interest around trajectory planning raises, in particular when a customer-oriented analysis is performed, since more and more the carmakers will have to pay attention to the handling comfort.
With that in mind, an experimental approach is proposed to assess the main characteristics of human driving and gain knowledge to enhance quality of autonomous vehicles. Focusing on overtaking maneuvers in a highway environment, four comfort indicators are proposed aiming to capture the key aspects of the chosen paths of a heterogeneous cohort.
The analysis of the distribution of these indicators (peak to peak lateral acceleration, RMS lateral acceleration, Smoothness and Jerk) allowed the definition of a *human drive profile*. These characteristics were then transferred to the simulation environment to create a pseudo-natural trajectory planning strategy, via polynomial fitting and spline optimization. This strategy differs from the standard approach of trajectory planning, where absolute minimums of cost functions are pursued.
The polynomial and spline fitting techniques reached satisfactory results and are evaluated as valid procedures to imitate a natural human behavior in a simulation environment (also applicable to control the trajectory of AD systems) and raise a question about whether a human-like behavior can be subjectively perceived as better driving, despite not presenting optimized comfort indicators.

Introduction

Autonomous Driving (AD) is one of the most prominent subjects of research and development in the automotive field of today. Side by side with electric and hybrid powertrain, light weight construction, connected vehicles and sharing economy, the development of self-driving vehicles has its place among the main trends in the next few years [2, 4-6]. SAE determines the intelligence level and automation capabilities of vehicles, ranking them from 0 to 5, being Level 0 (Fully manual vehicle) and level 5[th] (Human driving is eliminated) [1]. So far, only Level 4 (No human interaction required) autonomous driving have been completely achieved, and exclusively for closed traffic system, such as freeways. Urban traffic represents a more demanding challenge due to its complexity, such as pedestrian and non-regulated road condition. Therefore, as expected, the building of knowledge starts with more controlled environments, to then proceed to more intricate conditions.

Among the topics of interest, one particularly undecided is the standard (or most likely group of standards) to objectively distinguish between a *good* and a *bad* self-driving system. The current tests to assess the handling performance of an automobile are, justifiably, based upon the feeling and response of the driver [17]. Nevertheless, with the advancement of autonomous driving, this paradigm may shift towards a more comfort-based scenario. Certainly, comfort is already the subject of study of many areas within the vehicle design, such as NVH (Noise, Vibration and Harshness), but these areas should enlarge their scope to evaluate also the driving style and handling comfort of the autonomous vehicle. In another words, the burden of *bad driving* will be transferred from human to machine, compelling the OEMs to carefully take it into account. A specific topic that will help tackling this issue is the trajectory planning.
This paper has the objective of studying the handling comfort of overtaking maneuvers in a highway environment, to then build a notion around trajectory planning strategies, parameterized not by typical vehicle dynamics variables, but by comfort indicators. To do that, a group of comfort performance indicators and an experimental setup are proposed, as well as optimization and fitting techniques that will allow the evaluation of virtual trajectories.
Stepping in the state-of-the-art of science and engineering, the partnerships among carmakers and academic research groups shall be a valuable path to obtain important results. This paper shows an example of this kind of cooperation between FCA and the Politecnico di Torino.

Comfort Performance Indicators

The analysis of vehicle comfort performance for AD vehicles is a very challenging field, because of the novelty of this activity in the recent years. It is widely recognized, however, the importance of solid objective indicators to measure the comfort performance of systems.
Before presenting the indicators treated in this paper, it is essential to investigate the state of the art for the evaluation of the human comfort perceived.
Studies about human behavior and trajectory planning underline how human behavior [7] is strictly connected to the acceleration perceived and its variation, also known as *jerk*. It is reported in [8,9] that the human trajectory planning, in fact, follows the minimization of parameters similar to the jerk.
This aspect is reflected also in the choice of the cost function for the trajectory planning in AD systems; in fact, as it is described in [10] normal practice for trajectory planning is the use the cost functions about jerk minimization.

It is important to highlight the aspect of novelty of this paper, in which, beyond working on techniques to minimize such indicators, the human factor is experimentally evaluated to create a real (and in a further looking more *natural*) point of comparison to the ideal path. After this discussion, it is possible to show the indicators selected for this analysis:

- **Peak to peak values (p2p):** applicable to lateral acceleration, lateral jerk, steering angle and yaw rate, peak values have been selected because they represent the *impulsiveness* of the maneuver.
- **Root Mean Square (RMS):** also applicable to lateral acceleration, lateral jerk, steering angle and yaw rate, this indicator gives information about the performances among all the duration of the excitation on human bodies, like is typically done in NVH analysis.
- **Smoothness:** Smoothness instead comes from [11] where it was used to compare human and AI drivers, and it is defined as:

$$Smoothness^{-1} = \int_0^T \frac{\acute{\rho}(t)^2}{\sqrt{(\dot{x}(t)^2 + \dot{y}(t)^2)}} \qquad (1)$$

  Where: $\acute{\rho}$ is the derivative of the curvature and it is normalized according to the longitudinal speed of the vehicle. It is necessary to highlight that this indicator differs from RMS because the value is not divided by the time, so is just a sum of all discomfort issue happening during the maneuver.
- **Jerk cost function**: reflects this former aspect, in fact, as well as the Smoothness, is an absolute integral value without any time normalization. It represents the controller goodness, that is one of the possible cost functions that could be used in minimization algorithms. [7]

The use of yaw rate and steering angle, typically adopted in handling judgment, seems to be in opposition to the hypothesis of no distinction between driver and vehicle, since driving style is going to be an integral aspect of the car. In this scenario become necessary understand also the correlation between input and output and integrate the handling vehicle characteristic in the comfort evaluation process, and therefore these indicators are not included in the analysis.

Experimental Field

One of the targets of this paper is to assess the real performance of drivers in terms of comfort indicators, during overtaking maneuvers. The exploitation of this task has been performed starting form an experimental test campaign: more than 800 overtake maneuvers have been analyzed, thanks to the contribution of 7 different drivers (Table 1), running on two different vehicles. The 7 drivers (with different gender, profession, age and driver experience) were chosen to verify if those parameters generate variation in the driving style and if those differences could be appreciated through the selected performance indicators.

Table 1. Drivers' characteristics

Driver	Age	Gender	Occupation
Driver 1	20-30	M	Researcher
Driver 2	20-30	M	Student
Driver 3	20-30	F	Student
Driver 4	30-50	M	Researcher
Driver 5	50-70	F	Professor
Driver 6	>70	M	Retiree
Driver 7	30-50	M	FCA Technician

The scenario selected for those tests was the highway between Torino and Mondovì, because of its long straights and because in this segment the traffic conditions are not so heavy, allowing the execution of several maneuvers with certain freedom in choosing the trajectory. FCA provided the sensorized vehicles, and the procedure was simple: each driver must drive according to his personal style focusing the attention only on the speed limits and the other Road Laws.

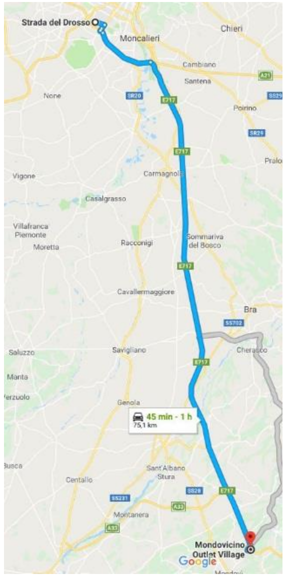

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Figure 1. The highway route used for road testing

No extra sensors, except a standard GPS antenna, were mounted on the vehicle. Most of the information had been collected from CAN network, through a CAN Network Logger. The vehicle dynamics data like accelerations, Yaw Rate, steering angle come from the sensors embedded on the vehicle, used by vehicle ECU to manage Passive Safety Systems like ABS and ESP. In Table 2 are reported the specification about the accuracy of sensors used.
All the data collected was used in the analysis, but for the evaluation of the different performance indicators on the maneuver the signal used were the lateral acceleration (form CAN Networks) and the speed (from GPS Antenna). The other information was used to get a check about the truth of acceleration and speed information and for the identification of overtake maneuver.

Table 2. Sensors specifications

Yaw rate [$\dot{\Psi}$]	Resolution	0.1		deg/s
	Measuring range	-100	+100	deg/s
	accuracy	-5	+5	%
	Noise RMS	0.1	0.2	deg/s

Lateral acceleration [a_y]	resolution	0.05		m/s^2
	Measuring range	-18	+18	m/s^2
	accuracy	-5	+5	%
	Noise RMS	0.05	0.1	m/s^2
Steering angle [δ]	resolution	0.1		deg
	Measuring range	-720	+720	deg
	accuracy	1.4	2.8	deg
GPS	Absolute positioning Accuracy (CEP)	3		m
	Relative Accuracy	0.01		%
	speed accuracy	0.5		km/h

GPS system, as descripted in Table 2 is not differential (as in DGPS) but its accuracy was enough to describe the trajectory, as can be seen from the blue lines reported in Figure 3. The absolute accuracy has lower importance respect to the relative accuracy, since the main interest are brief maneuvers. The trajectory have been derived directly form geometric transformation from Latitude and Longitude coordinates, expressed in Equations (2) and (3).

$$X = \sqrt{\frac{R*\cos(lat)*\cos(lon)}{1-e^2*\sin(lat)}} \qquad (2)$$

$$Y = \sqrt{\frac{R*\cos(lat)*\sin(lon)}{1-e^2*\sin(lat)}} \qquad (3)$$

Where: *lat* and *lon* stand for latitude and longitude coordinates converted in radians, *R* is the Earth radius and *e* the Earth eccentricity.
Looking to the testing procedure, in Figure 2 is reported a schematic representation of the maneuver that drivers should execute with the relative nomenclature choose for the different phases of the maneuver.
The criteria for the extrapolation of the different maneuver are crucial to have a correct evaluation of the lane change especially in the cumulated index. In fact, the addition of noise component coming from straight parts would return a higher value of the indicators that does not reflect the actual discomfort level of the maneuver.
Nowadays it is very difficult to gather a standard criterion regarding the definition of lane change, in terms of cut-out start and cut-out end for experimental road tests.
A specific procedure, based on internal reference and correlations of the available data, has been proposed and used. In particular, the analysis was focused on the first lane change that have been called *cut-out* maneuver. In the post-processing analysis, the cut-out start was identified as 1,5 s before the motion of the steering wheel from the cruise position (that was approximately centered, except from some specific parts of the road with bends of very large radius) to an angle superior to 0.2°. The cut-out end was defined looking at the yaw rate finding the first moment followed by a stabilized part, objectively traduced to a stable interval (ranging between ±0.25 deg/s) for at least 0,8 s. When it was reached a stable value, around the null rotation, it means that the vehicle is running again on a straight segment, so the maneuver can be considered as expired. In this step the use of trajectory from GPS was crucial to check if the cut-out maneuver limits have been defined correctly.
Figure 3 shows the main variables considered in the analysis of one particular maneuver: In particular: Trajectory (lateral displacement) from GPS (blue line); Cut-out start and cut-out end (black solid dots); Steering wheel threshold position (red solid dots); Longitudinal speed of the vehicle throughout the maneuver (up-left plot); Steering angle (red line) and the moment in which it overcomes the threshold (black circle in the up-right plot); Time history of the lateral acceleration and of the yaw rate (low-left and low-right plots respectively). In the yaw rate outline, it is possible to appreciate that the end of maneuver corresponds with a stabilized signal.

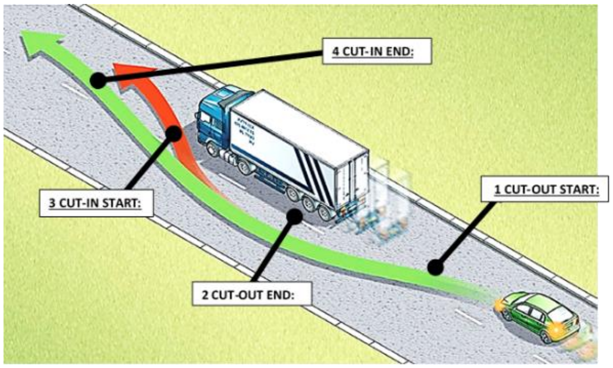

Figure 2. Maneuver summary

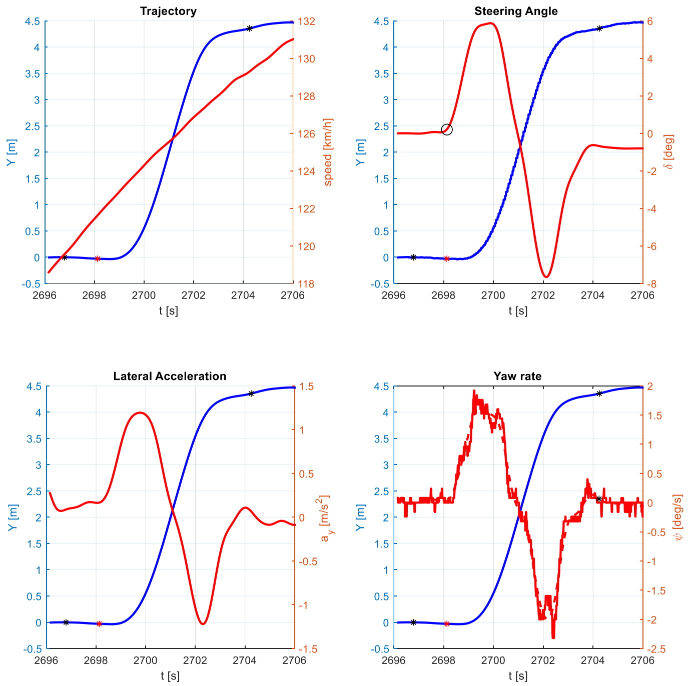

Figure 3. Example of lane change with cut-out extrapolation criteria

Experimental Results and the Human Driving Profile

Once the overtake maneuvers were identified among the raw data, the indicators presented before were evaluated and used for the classification of the different overtakes, selected among all the drivers that performed this experiment.

Figures 4 and 5 show some relevant results. In figure 4 is represented for each overtake maneuver the smoothness (in blue) and the peak to peak indicator (in red) related to the lane change duration. Looking at those indicators and their distribution, it can observed a wide range of results with no apparent correlation between the factors. This correlation could be expected since a longer maneuver theoretically demands higher accelerations and a less smooth path to be completed, but it became clear that other factors not connected with the elapsed time have bigger influence.

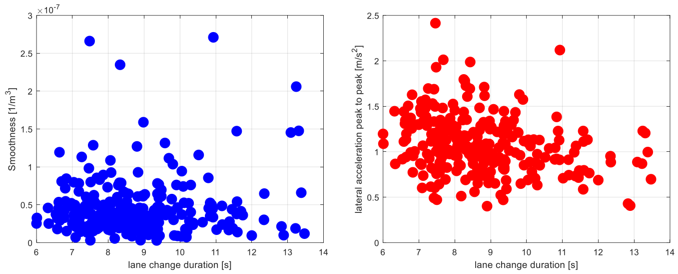

Figure 4. Comfort indicator vs. duration of the cut-out plot: smoothness (left) and p2p lateral acceleration

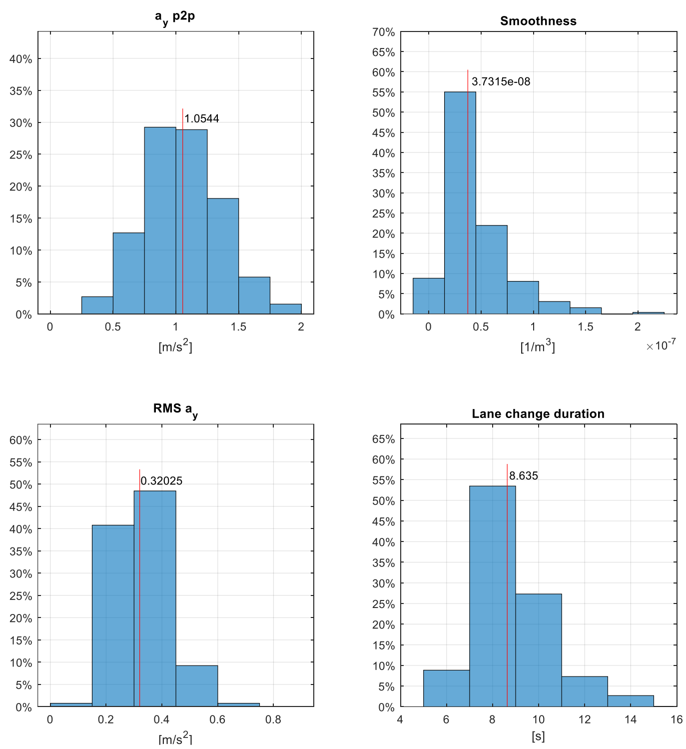

Figure 5. Experimental classification

Several stratifications were performed to come up with systematic differences and correlations based on gender, age, experience, occupation and so on. Nevertheless, the widespread shape of the distribution is maintained across the various segmentations.
Figure 5 reports the distribution of three performance indicators and the duration of the cut-out.
Most of the maneuvers tends to be grouped around a central value (median), corresponding to the red line. This relative concentration is useful to build a point of comparison for the *human driving profile* described as function of the perceived handling comfort of the overtake.

This notion has two main possible applications: to serve as point of comparison (or even minimum acceptable performance) for the development of AD vehicles and assess their expected perceived handling comfort; or to be a *target* for AD systems that would not be focused on minimize the indicators, but to imitate the natural behavior of a normal driver.
The former is most intuitive path to take (and indeed, the great part of articles discussing trajectory planning aim to overcome human performance with mathematical optimization), since the latter would implicate some sort of evidence that a *natural* maneuver is perceived as better despite its not-optimal comfort indicator. However, as an academic investigation, it is thought provoking to pursue an alternative way and try to replicate the experimental data with artificially created trajectories based on the comfort indicators as tuning parameters, giving the paper a novelty factor and opening a thread of research that might find some worthy future developments.

Trajectory planning and Minimization Algorithm

Starting from experimental data and its analysis, the attention is briefly shifted to simulation and mathematical environment to define a robust trajectory planning algorithm capable to work according to the guidelines provided by the real human profile.
Before starting to the comparison of the virtual trajectory and the real trajectory may be interesting to spend some words about trajectory planning. This is a widely explained topic, several papers have been produced like.[12–16]
The first approach used for trajectory planning is a simple fifth order polynomial Equation (4), because it is more robust in terms of simplicity and in terms of mathematical properties, (for example a polynomial is always continuous and derivable).

$$y(t) = a_0 + a_1 t + a_2 t^2 + a_3 t^3 + a_4 t^4 + a_5 t^5 \quad (4)$$

The general idea in this case is to evaluate the coefficients to obtain a mathematical description of the trajectory. For this reason, it is generally necessary to fix the boundary conditions and solve analytically the problem.
In literature, it is possible to find several examples [16] where it was enough to fix just speed and position at the begin and at the end of the maneuver as boundary conditions to define the trajectory.
Moreover, in this case study, this approach is not enough, so two more constraints are requested by the higher order. The solution was the definition the values of accelerations at the boundaries. As a result, the boundary condition selected in the first part of the study were the following:

$$\begin{cases} y(0) = 0 \\ \dot{y}(0) = 0 \\ \ddot{y}(0) = 0 \\ y(\tau) = W \\ \dot{y}(\tau) = 0 \\ \ddot{y}(\tau) = 0 \end{cases} \qquad (5)$$

Where W is the width of the lane and τ is the duration of the maneuver. Eq (5) refers to lateral motion and it correlates to the longitudinal speed profile. For the sake of simplicity, it is supposed henceforward that the ego vehicle keep constant speed motion along the x-direction.
The analytical solutions of (4) through the six boundary conditions (5) bring to the definition of the different coefficient "a_i" of the polynomial equation. The result at this point is parametric since the

time duration of the maneuver τ is not defined. At the end this is the only parameter that can be arbitrary chosen, so it is the only DOF that can be used for trajectory tuning, using this approach.
In Figure 6, it is possible to appreciate this parameterizations since they are represented 3 trajectories with 3 different values of τ. It is possible to note how the duration of the lane change can affect the result, but it is clear that this unique DOF allows extending the trajectory improving comfort but without any change in the shape.
This unique DOF represent a drawback when a fitting procedure it is required, because for example it is possible, for example, to impose a certain value for the acceleration p2p value (correlated directly to τ), but all the other maneuver characteristics are constrained.
For this reason, it was realized that more flexibility had been required in order to fit experimental data, so the attention was shifted to the possibility to investigate different shapes introducing a more complex algorithm for the trajectory definition.

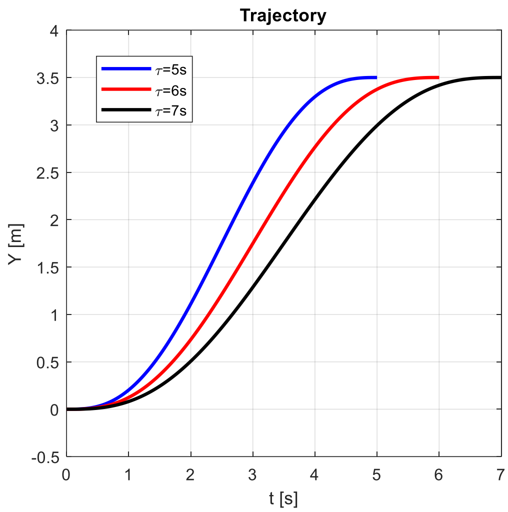

Figure 6. Polynomial trajectories

A possible solution could be to define no more a single polynomial but a spline and consequently the analytical solution became no more available. This is the reason why the solution adopted for the virtual trajectory planning was a fifth order spline evaluated through the minimization of a cost function.
The introduction of the spline in fact allow the use of N DOF, the number N represent the number of points (called Nodes) where the spline must pass through.
To overcome the absence of a single mathematical solution and get a description of a trajectory trough a polynomial spline, it is necessary the application of a minimization problem according to a cost function. This approach has been used in several case studies like [7,10,16] and according to [8] the best cost function.
As disclaimed before those algorithms are generally built up to get an optimum related to the minimization of the lateral acceleration or the jerk. Nevertheless, in this case study, the target is the *replication* in virtual environment of a trajectory coming from experimental data. Consequently, it was built up a cost function (Equation (6)) that starting from a generic spline is changes it shape in order to minimize the gap from the average data collected and fitting experimental data as much as possible.

$$y(t) = \begin{cases} a_{00} + a_{01}t + \cdots + a_{05}t^5 \; t < t_{10} \\ a_{10} + a_{11}(t - t_{10}) + \cdots + a_{15}(t - t_{10})^5 \; t_{10} < t < t_{20} \\ \cdots \\ \cdots \\ \cdots \\ a_{n0} + a_{n1}(t - t_{n-1}) + \cdots + a_{n5}(t - t_{n-1})^5 t_{n-1} < t < t_n \end{cases} \tag{6}$$

Large differences among the various maneuvers have been noted as well as the random error of GPS introduced unexpected deformations (sometime some spikes have been noted in the signal). For this reason, to identify a possible average maneuver from experimental data, the solution was to define the ideal trajectory on the base of the performance indicators rather than its shape.
The mathematical tool that has been used was the optimizer block, showed in Figure 7, of Altair Activate. It receives as input the spline N nodes that are shown in Figure 8, that those nodes are interpolated using a fifth order spline, like the one in (6), to get the trajectory. Smoothness, acceleration peak to peak and RMS are evaluated, the square difference among those indicators and the experimental average represent the cost function that was minimized by the software.
The optimizing loop process is stopped once a local minimum is reached. In this specific case the loop is stopped after about 10^5 iterations with the same value up to the 5th significant digit. In this way, there are N DOF where N is the number of nodes as it is possible to appreciate from Figure 8 and this allows to define the optimum shape.

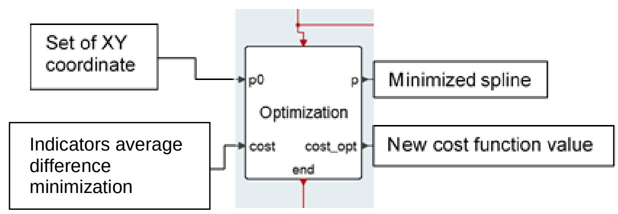

Figure 7. Scheme of the minimization algorithm

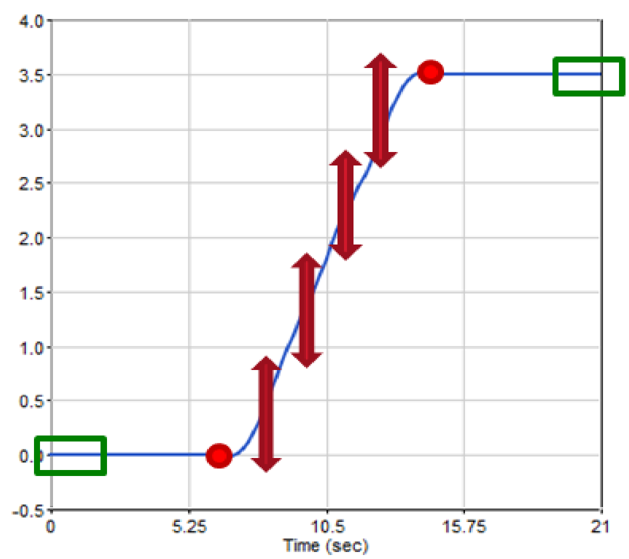

Figure 8. Spline DOF and main features

To improve performance and efficiency of simulation it was crucial to reduce as much as possible the constraints that the software must consider in the optimization process. The set of points was redefined

imposing the clamped boundary condition on two straight parts before the actual lane change (represented by the green squares). The red points are the limits of the lane change start and end; while the N point in the middle (schematized with red arrow) are free to move according to the algorithm process.
The results are showed in Figure 9 and as can be seen, give important hints about which shape reduce the minimum the cost function so under the hypothesis of this case study is the best according to comfort. It is interesting to focus the attention to the fact that the shape is changed from the single polynomial since the comfort optimized spline is no more symmetric and show small overshoots at the beginning and at the end. This aspect has been commonly found also in experimental trajectory, the black line, in fact, comes directly from the experimental maneuver average and shows this tendency. Those overshoots have been investigated in dept and the conclusion of the study was that actually drivers tend to naturally execute this kind of maneuver even if they reduce it as much as possible.

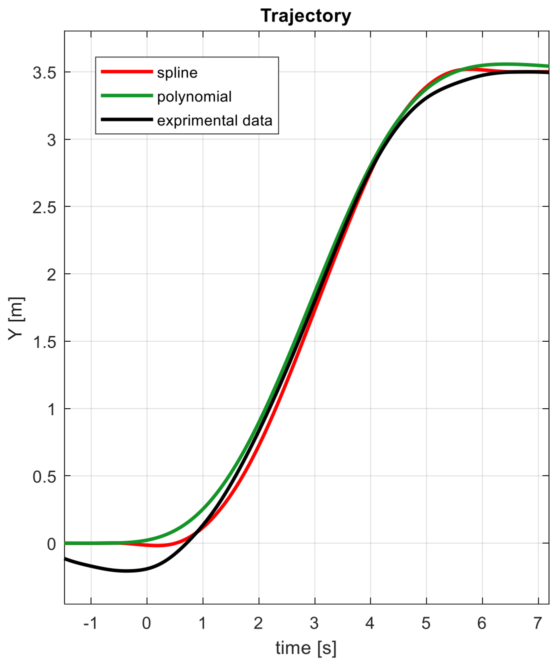

Figure 9. Trajectory comparison

Numerical vs. Experimental Trajectories

From virtual trajectory tuning activity, it is possible to conclude that even if from experimental data post processing it wasn't possible to identify an average shape and the virtual trajectory had to be developed using the indicators it is possible to find some connection among virtual and experimental ones like the overshoot and the not symmetric lane change.
The use of spline increase complexity but provide a more tunable result. The point is now to evaluate an average maneuver that can in such a way summarize all the overtaking maneuvers collected up to now. In this way, it is possible to have a virtual trajectory that can represent the experimental data. For sure is not easy to get a correct average of everything; starting from figure 10 it is possible to appreciate that a large part of maneuvers are in the range of 6-9 seconds with a certain value of discomfort expressed thanks to the value of the smoothness or the lateral acceleration peaks or even the RMS.

It was discussed how the spline trajectory because of its better tunability can describe a wider typology of trajectories allowing to get theoretically several different shapes. Nevertheless, the question at this point is to understand which kind of trajectory can be more representative of the maneuver collected during the experimental test.

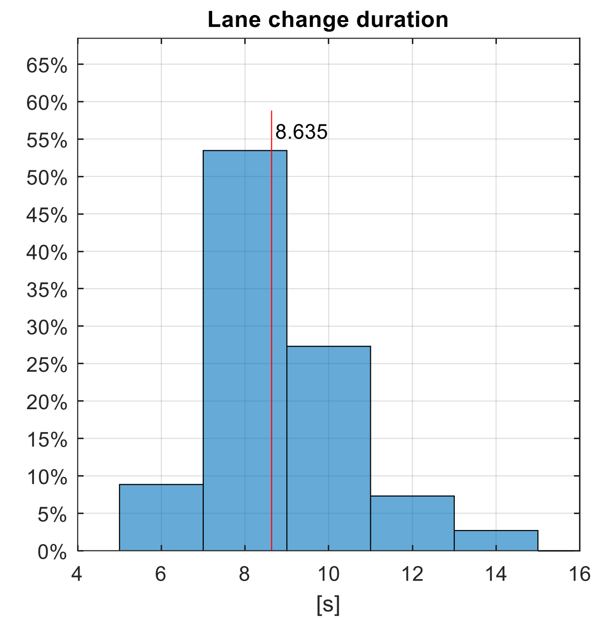

Figure 10. Maneuver duration

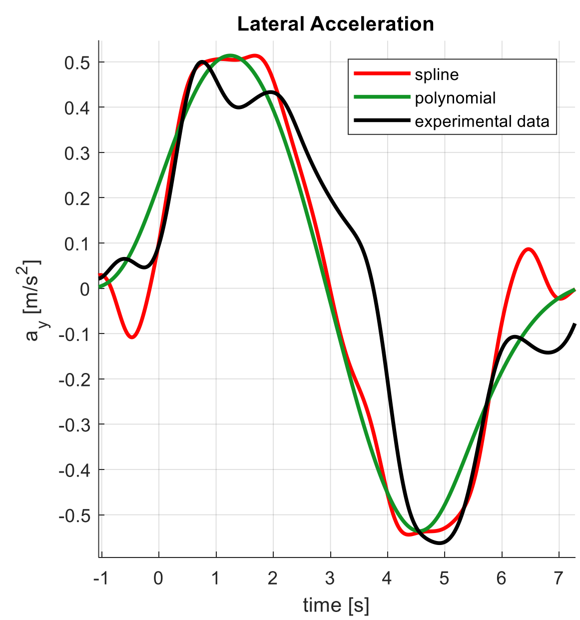

Figure 11. Simulation acceleration profiles

Figures 11 and 12 show a comparison among simulation and real a profile in terms of lateral acceleration and trajectory. It is possible to understand how the spline trajectory trajectories could be more representative of a real profile respect to the polynomial.

The reason is obvious related to the higher degree of freedom allowed by spline trajectory respect to the polynomial where it is only possible to tune the duration to fit just one parameter.
So, the focus have been shifted to the performance indicators evaluated for both trajectories typologies compared with experimental data and shown in Figure 12 to understand which simulation are more in line with experimental results.

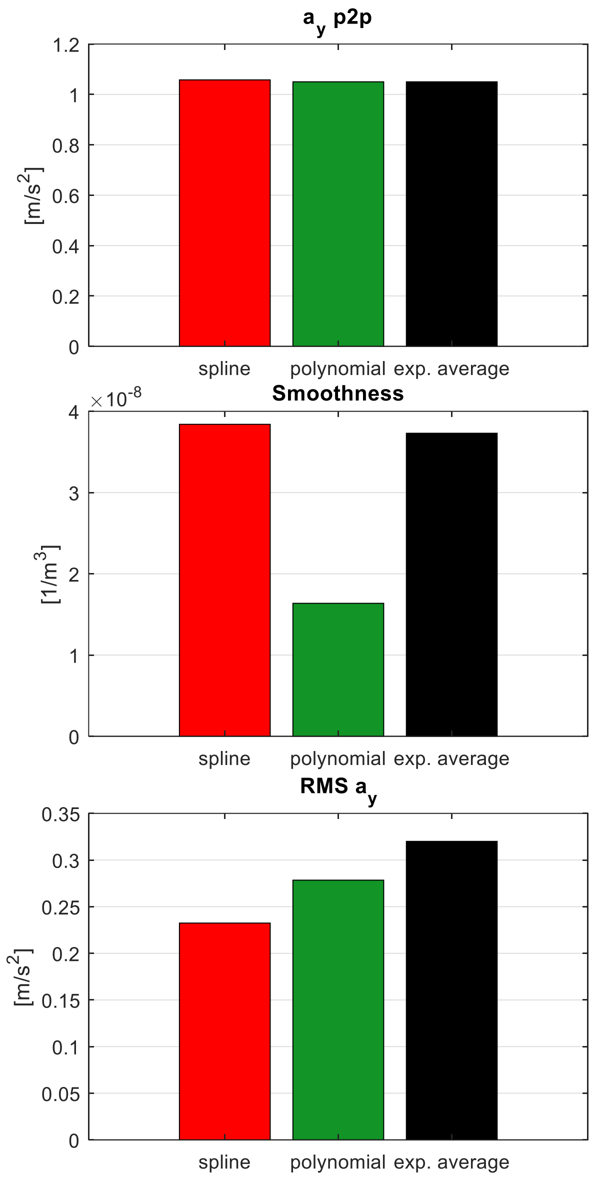

Figure 12. Simulation indicators compared with experimental ones

The same tendency is confirmed also with this analysis where spline performance indicators appear more in line with experimental data. Some major differences have been reported by RMS, the hypothesis is that these indicators may include some noise related to external excitation phenomena like wind, wake or other aerodynamic effect or ground irregularities that cannot be reproduced in virtual environment. Both methods are reliable and perfectly suitable to the implementation in simulation environment, with some benefits and drawbacks.
On one side it was demonstrated that in terms of fidelity the spline must be preferred, basically because of the overshoot and non-symmetric behavior. While for preliminary computation, the best approach should be the single polynomial expression because of its simplicity.

Conclusions

This paper has the objective of studying the handling comfort of overtaking maneuvers in a highway environment, then, building a know-how about trajectory planning strategies, parameterized not by typical vehicle dynamics variables, but by comfort indicators. The motivation to do so, is to strengthen the knowledge around Autonomous Driving Trajectory Planning with a customer-oriented mindset, a strategy considered essential since the vehicle is going to be also responsible for the ‘bad driving’ discomfort.
Taking advantage of the partnership between FCA and Politecnico di Torino, an experimental setup was developed and more than 800 overtakes were recorded. The cohort included drivers with high heterogeneity and a simple experimental procedure was imposed to permit the most natural behavior of the drivers in terms of style and trajectory planning. Using objective post-processing strategies, the raw data was treated, and the authors were able to identify the maneuvers and classify them in terms of four main comfort indicators: peak to peak lateral acceleration, RMS lateral acceleration, smoothness and jerk.
Analyzing the distribution of these overtakes, the authors were not capable of find any statistically relevant correlation between comfort and the characteristics of the drivers, neither between factors such duration of the maneuver or longitudinal speed. Nonetheless, the histograms show a clear concentration of the indicators around the median value, indicating that these values can be representative of a *human driving profile*.
At this point it was decided to pursue an alternative path to the paper: instead of creating trajectory planning strategies to optimize the comfort indicators (as performed countlessly by other studies) and compare them with the experimental data, the authors used the natural driving parameters to tune the trajectories and artificially build a pseudo-natural path. The polynomial and spline fitting techniques reached satisfactory results and are evaluated as valid procedures to imitate a natural human behavior in a simulation environment (and therefore also applicable to control the trajectory of AD systems). It is yet to be defined if this methodology shall bring any advantages in terms of subjective evaluation of AD handling comfort.
Future works can help answering the two important questions that remain: Are there external or internal factors that allow to explain and correlate the widespread data of experimental comfort indicators? Can a pseudo-natural trajectory based on the *human driving profile* be perceived as better than an optimized trajectory.

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Definitions/Abbreviations

ABS	Anti-lock Braking System
AD	Autonomous Driving
ADAS	Advanced Driver-Assistance Systems
CAN	Controller Area Network
DOF	Degree of Freedom
DGPS	Differential Global Positioning System
ECU	Electronic Control Unit
ESP	Electronic Stability Program
GPS	Global Positioning System
FCA	Fiat Chrysler Automobiles
IT	Information Technology
NVH	Noise and Vibration Harshness
P2P	Peak to Peak
RMS	Root Mean Square
SAE	Society of Automotive Engineers