The Influence of Lane Width on Semi-Autonomous Vehicle Performance

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ABSTRACT

In a medium-term, the number of semi-autonomous vehicles is expected to rise significantly. These changes in the vehicle capabilities makes it necessary to analyze their interaction with road infrastructure, which was developed for human-driven vehicles. Current systems use artificial vision, recording the oncoming road and using the center and edgeline road markings to automatically facilitate keeping the vehicle within the lane. In addition to alignment, as well as to road markings, lane width emerges as one of the geometric parameters that might cause disengagements and has to be assessed.

The objective of this research is to study the impact of lane width on a semi-autonomous vehicle performance. The automatic lateral control of this type of vehicle was tested using one of them along 81 lanes of an urban arterial, with diverse widths. Results showed that the semi-autonomous system tended to fail at narrow lanes. There was a maximum width below which human control was always required – named human lane width – measuring 2.5 m. There was also found a minimum width above which automatic control was always possible – named automatic lane width – and established in 2.75 m. Finally, a lane width of 2.72 m has the same probability of automatic and human lateral control – named critical lane width.

Following a similar methodology, these parameters can be determined for other vehicles, enhancing the interaction between AVs and road infrastructure and thus supporting a fast deployment of autonomous technology without compromising safety.

Keywords: Lane width, CAV, Semi-autonomous vehicle, Lane Keeping Assist, Automatic lane width

INTRODUCTION

The number of semi-autonomous vehicles is on the rise. With increasing technical capabilities and efforts by the Original Equipment Manufacturers (OEMs) and public administrations, these vehicles are expected to dominate the market in five years, despite cyberattack and safety concerns (1). The European Commission has recently included a new policy action with a strong focus on a comprehensive framework for connected (2) and automated driving (3), requiring all new marketed vehicles by 2022 to be semi-autonomous. All these actions help fostering the deployment of full-autonomous vehicles, although this scenario is still unforeseeable in an accurate way (4).

The Society of Automotive Engineers (SAE) scaled automated driving systems from 0 to 5 (5) as a function of how driving negotiation is controlled by the system (longitudinal and/or lateral), fallback response, and Operational Design Domain (ODD). An ODD is defined as the circumstances under an Autonomous Driving System is designed to operate.

In automation level 2, the vehicle can control both longitudinal and lateral negotiation. However, level 2 systems are not perfect and occasionally fail at perceiving/interpreting the road path, giving the control to the driver in what is called a disengagement. This is why the human must always be monitoring the system. Automation level 3 goes a step further, only requesting take-over by the driver for fallback response. A level 4 semi-autonomous driving system should be able to take control of the vehicle under a given Operational Design Domain (ODD), continuously and uninterruptedly. Current marketed vehicles may reach level 2 and, under certain limited operational domains, level 3.

Since these systems require continuous human presence and monitoring, a Human-Machine Interface (HMI) is needed. This interface alerts the driver when a disengagement occurs (level 2) or their intervention is about to be required (Take-Over Request, TOR) (level 3) (6). Unfortunately, existing semi-autonomous systems are in an early development stage and disengagements are relatively frequent. This may end into the drivers not willing to activate the system, or eventual surprises caused by unexpected disengagements – which might be risky, since it increases drivers' response times (7,8). The effect of these failures is higher as the system is more intervening on the driving task. In addition, the HMI warnings are often quite subtle, given their relative frequency.

Semi-autonomous driving automation systems use center and edgeline road markings to automatically facilitate keeping the vehicle within the lane. There are different technologies to assist drivers in negotiation: Lane Departure Warning (LDW, it warns the driver if the vehicle is to leave the lane), Lane Keep Assist (LKA, in warns the driver and performs slight steering movements to avoid leaving the lane), and Lane Centering Assist (LCA, the system completely negotiates the vehicle direction following the lane path). In addition, there are many different technologies behind these Advanced Driver Assistance Systems (ADAS), with different performance outcomes.

Despite the technological variability across systems, most of them are based on digital image processing, given the higher cost of other systems with good results (9). This system normally uses video cameras to record the oncoming road path. Artificial vision systems must process a large amount of information per second, in real time and with high reliability. For that purpose, the information is generally first cropped to a certain Region of Interest (RoI). Every photogram will be further decomposed into matrices, being the HSI system the most general one (10). Each one of these matrices is then processed to detect object boundaries and textures. Classic edge detection algorithms compare adjacent pixels, while ridge-type algorithms use more pixels and give better results (11).

This is a critical process, since road markings might not be in good state, thus leading to unclear zones, or shady areas that are difficult to be interpreted as a road marking. Cácere et al. proposed a methodology to overcome this limitation, based on an RGB filtering followed by an intensity clustering (12).

With this information, another algorithm depicts a polyline centered in each road marking, and inverse conic restitution is later applied (9), taking the visualized road markings and projecting them into a X-Y reference. Besides the correct detection of these lines in every photogram, it is necessary their temporal comparison, checking that the geometry from consecutive photograms is consistent (9). In most cases, stochastic methods are used.

Some methodologies may be applied in this step, to increase the reliability of the result and/or alleviate the processing requirements. These kinds of methodologies help the system when encountering confusing zones. Some of them compare the layout of the boundary lines that conform a lane (which should be parallel in nearly all situations). Du and Tan applied a ridge detection methodology for this purpose (11), after enhancing the quality of the photograms with several filtering processes.

The relative position of the vehicle is also very important. Its position is normally determined based on inverse conical restitution, but more advanced systems such as stereoscopic vision and a helping camera are currently under development (9).

Many disengagements and take over requests are caused by an impossibility of clearly tracking road markings or a misinterpretation of road geometry. This may partially be explained since the remarkable advances in vehicle automation are not being developed in line with road infrastructure and regulations (13, 14, 15).

Harmonization and update of regulations to consider both human and autonomous vehicles would help at minimizing some disengagements. This would require more information about what aspect triggered the disengagement but given the variety of systems and the limited information available, it is sometimes very difficult to know it. This is why the authors have focused on developing methodologies to test how well a certain driving automation system adapts to road infrastructure, regardless its underlying technology. This information would help to a) establish a clear benchmark for OEMs to develop their systems, and b) shorten the path towards SAE level 4 systems and adequately defined ODDs.

In recent studies, the authors explored the geometric-related limitations of a driving automation system, showing a clear relationship between speed, geometry and disengagements (14). They also studied how the same driving automation system responds to existing edgeline road marking gaps (such as those present at exit, entrance ramps, lane merging and so on) (13). It was observed that near 25% of entrance and exit ramps caused the system to fail, as well as diverging, merging sections, and similar ones (**Figure 1**).

Figure 1 Freeway lane reduction losing the continuity of one of the edgeline road marking

OBJECTIVES AND HYPOTHESIS

The literature review allowed to establish the scope for this research, not having found experimental studies about the impact of the lane width in the performance of automatic lateral control. The objective of this research is to study the impact of lane width and road marking layout on a certain Lane Keeping Assist (LKA) system. The main hypothesis is that a wider lane increases the reliability of this autonomous driving system. To check that, a single semi-autonomous vehicle was tested along some tangent sections of urban streets, with different lane widths and road marking patterns.

This paper develops a methodology to test the performance of a semi-autonomous vehicle as a function of lane width. Although the numeric results can only be applicable to the tested vehicle, the same methodology can be extended to other systems with probable different limitations. This will have important implications, as mentioned in Discussion and Conclusions sections.

METHODOLOGY

To perform the objective, one semi-autonomous vehicle with automation level 2 was driven throughout 12 arterial tangent sections, belonging to a 5.4 km long urban arterial ring road in Valencia city (Spain). The road presents two directions, with several lanes with diverse lane widths, ranging between 2.28 and 3.80 m (2.70 m on average). The total number of observed lanes was 81, all located at tangents (**Figure 2**). The lane width distribution is shown in **Figure 3**.

Figure 2 Observed lanes located on 12 transversal sections along the North arterial ring road of Valencia

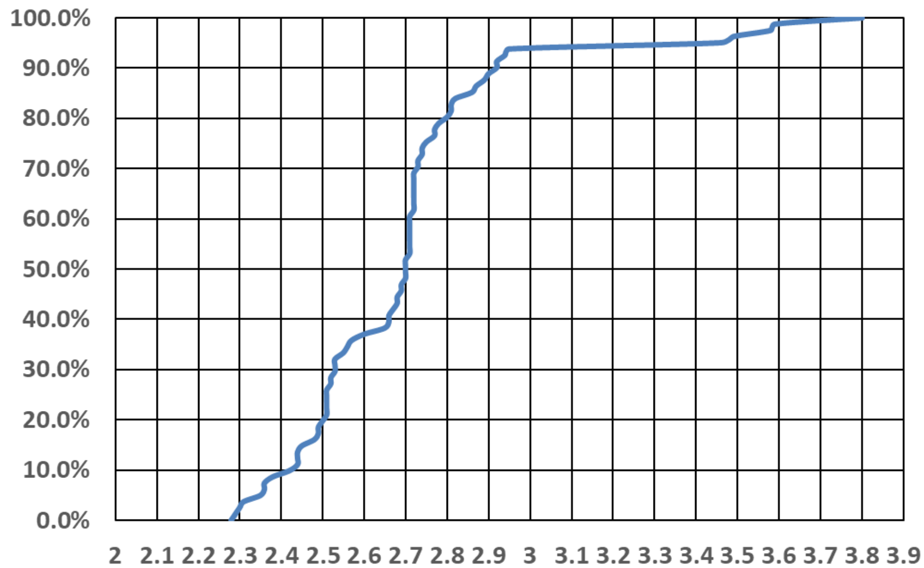

Figure 3 Lane width distribution

The same driver performed all tests with the same semi-autonomous vehicle (BMW 520d, manufactured in 2017 and equipped with the package Driving Assistance Plus, with Adaptive Cruise Control (ACC) and Lane Keeping Assist (LKA) as two of the main ADAS). With both systems activated, the vehicle takes control of acceleration, brakes and steering, keeping the vehicle within the lane thanks to center and edgeline detection by means of two video cameras located behind the inner mirror.

The vehicle was also equipped with a HD video camera with GPS. This camera was mounted besides the driver's head, for simultaneous recording of the roadway, navigation map, dashboard, hands position on the steering wheel, and the driver's comments (**Figure 4**).

Figure 4 HD video camera for observations (left) and screenshot from it (right).

Being automation level 2, the driver is required to continuously monitor the system. This is ensured by asking for permanent contact with the steering wheel – although hands can be released for a few seconds, before the system emits an aural warning.

By means of sensors, the system is capable of tracking the ongoing lane, as well as the surrounding objects and vehicles. The system controls the vehicle with all this information. If any error, inconsistency or confusion takes place within the process, the system transfers control to the driver with a visual – but not aural – warning.

The minimum number of passes along every lane was 10, driving near the speed limit (50 kph) at daytime and under good weather conditions. Looking at the video-camera recordings, it was possible to determine for every section, lane and pass whether the automatic lateral control performed or transferred control to the driver (1: automated system works; 0: the automated system releases control). Subsequently, the performance rate of the system was averaged for every section and lane. **Table 1** summarizes results for all six lanes of section 2. Similar tables were developed for the rest.

TABLE 1 Observed performance results

SECTION	CARRIAGEWAY DIRECTION (E/W)	LANE (Left=1;2;3;4;5)	WIDTH (m)	TRIP										LKA RATE (Y=1; N=0)
				1	2	3	4	5	6	7	8	9	10	
A2	W	3	2.94	1	1	1	1	1	1	1	1	1	1	1.0
A2	W	2	2.89	1	1	1	1	1	1	1	1	1	1	1.0
A2	W	1	2.60	0	1	1	1	1	1	1	0	0	0	0.6
A2	E	1	2.50	1	0	0	0	0	0	0	0	0	0	0.1
A2	E	2	2.90	1	1	1	1	1	1	1	1	1	1	1.0
A2	E	3	2.92	1	1	1	1	1	1	1	1	1	1	1.0

RESULTS

Figure 5 depicts the automatic and human lateral control rate for every lane, as a function of the lane width. The main hypothesis is confirmed, since the automatic lateral control rate increases with the lane width. On the contrary, the human lateral control rate decreases.

The human lateral control was totally prevailing under 2.5 m wide. This new concept – maximum width for which steering control is 100% human – is defined as **human lane width**.

In addition, the automatic lateral control was 100% effective above 2.75 m wide. The **automatic lane width** is therefore defined as the minimum width for which the steering control can be 100% fulfilled by this driving automation system.

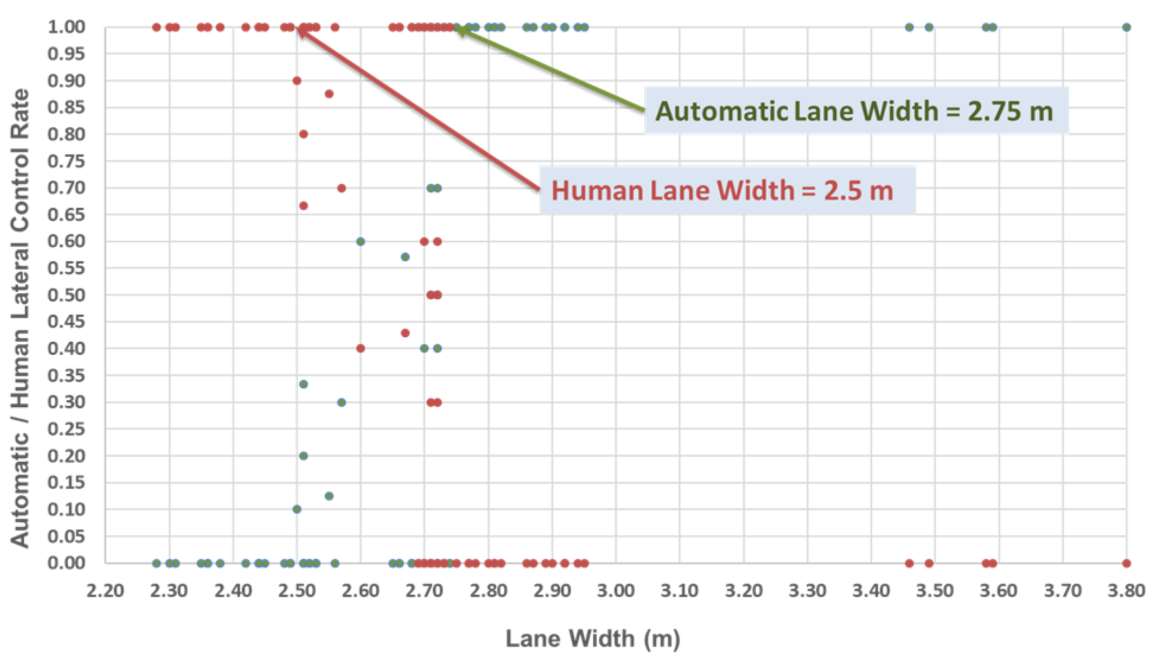

Figure 5 Observed lateral control performance by lane width

DISCUSSION

Human and automatic lane widths reveal as crucial factors for automotive industry and infrastructure design. Conversely to other design factors such as horizontal and vertical geometry, the narrow interval between both thresholds reveal the strong and undesirable effects that subtle design actions might have on autonomous driving.

Figure 6 summarizes the human and automated lateral control rates in 5 cm bins. The abovementioned performance is observed, and the **critical lane width** can be calculated as the intersection of both lines, being the width that presents the same probability for human and automatic lateral control, determined at 2.72 m.

Thus, a vehicle with the same dimensions and this driving automation system would perform as a function of the lane width as follows:

- Lanes narrower than the human lane width: the system cannot perform in autonomous mode.
- Lanes between the human lane width and the critical lane width: the system generally disengages but might sometimes track the road path if all other conditions are favorable.
- Lanes between the critical lane width and the automatic lane width: the system generally tracks road geometry, but might eventually disengage (not perfect road marking, presence of dust/shadows on the road, etc.).
- Lanes wider than the automatic lane width: the system is capable of track the road in an autonomous way (as long as other factors are also compatible with the system).

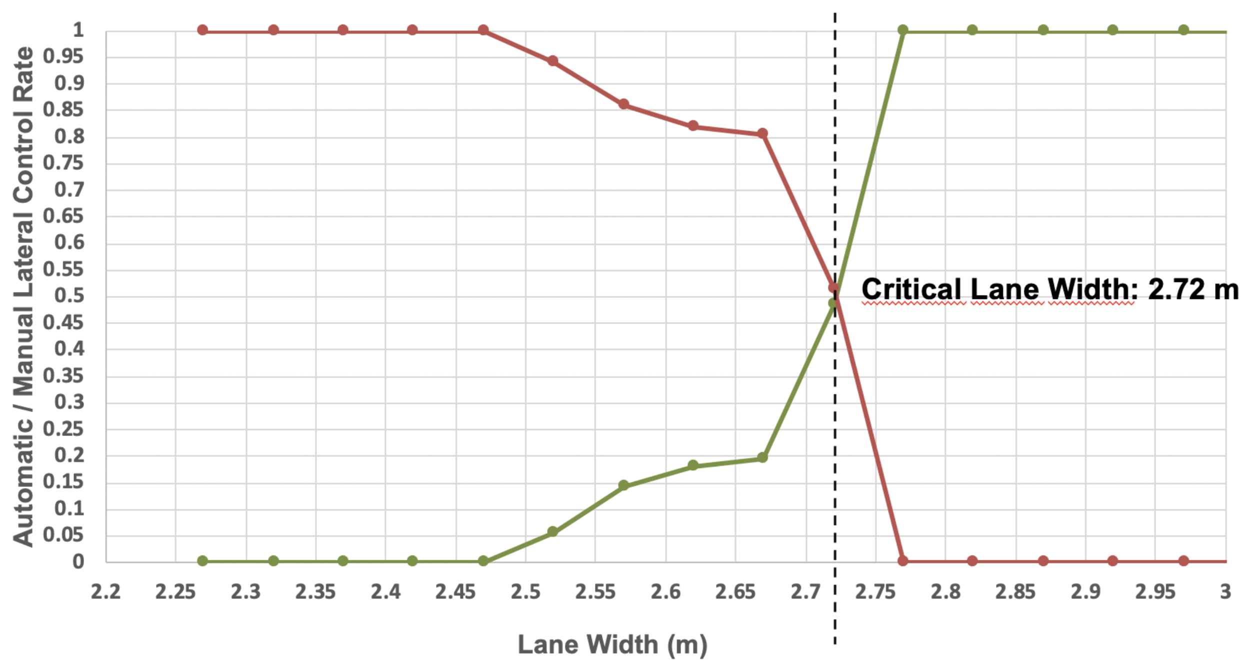

Figure 6 Critical lane width

Taking into account the observed automatic lane width and the width of the experimental vehicle, the tested vehicle needs a free lateral space of 0.88 m (0.44 m per side if completely centered) (0.62 m, 0.31 per side considering mirrors) (Figure 7).

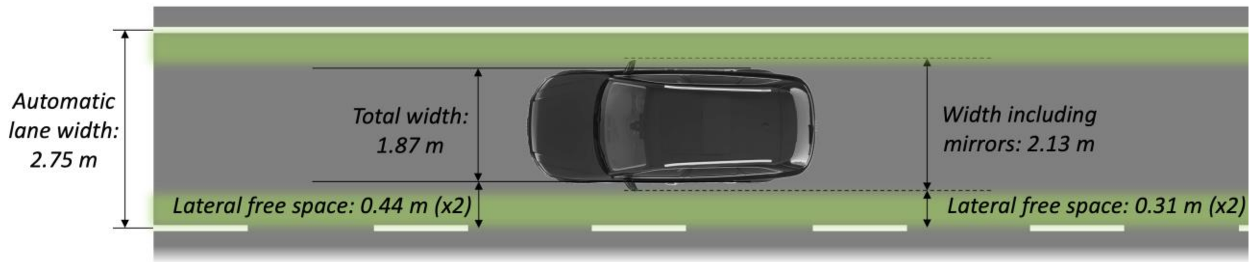

Figure 7 Vehicle dimensions and free lateral space.

The aim of the paper was to provide a framework to test lane width-related disengagements without considering the vehicle technology. Thus, the technology-related causes triggering disengagements that take place at narrow lanes remains unknown. Two alternative potential explanations are provided therefore:

- The visual subsystem cannot perceive/process narrower lanes in an accurate way. In this case, other vehicles with the same driving automation system would present the same limitation regardless their dimensions (including heavy vehicles).
- The driving automation system requires some free space for steering. In this case, other vehicles with the same driving automation system would require lanes wider than $v_{w,m}$ + 0.62 m and $v_{w,nm} + 0.88$, where $v_{w,m}$ is the width of the vehicle including mirrors and $v_{w,nm}$ is the vehicle width without mirrors. This would set a minimum lane width of 3.43-3.48 m to accommodate autonomous heavy vehicles (Figure 8).

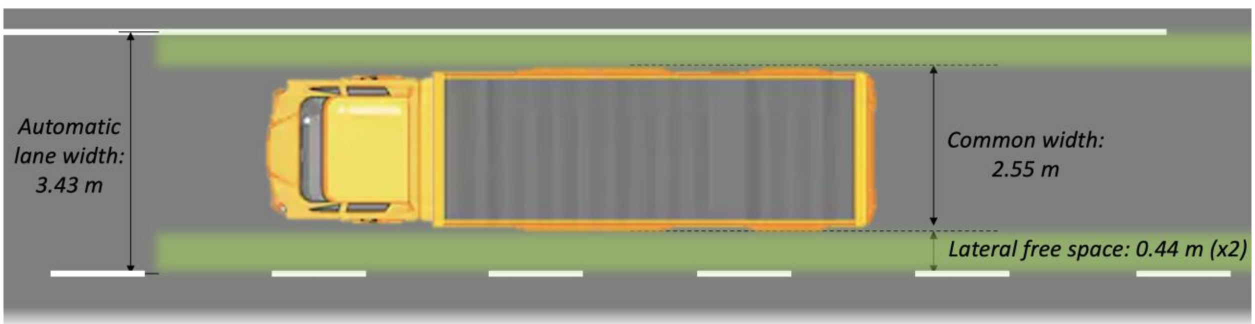

Figure 8 Minimum requirements for a heavy vehicle using the same driving automation system.

To summarize, these findings clearly define 2.50 m to 2.75 m as an Operational Design Domain threshold for this driving automation technology. Other systems could be tested following a similar methodology, hence determining the lane width they require to fully perform autonomously (again, as long as other limiting parameters are met). HD GPS maps should therefore include information about the lane width, allowing any driving automation system to compare it to its limitations.

For autonomous heavy vehicles, their automatic lane width might define another ODD threshold (around 3.40-3.50 m). From a design perspective, dedicated lanes for automated heavy vehicles could be proposed, increasing road capacity. At this point, it would be necessary to force harmonization of the driving automation system capabilities to these widths. Dedicated lanes for light vehicles could be designed following the same principle, as well.

Finally, it is necessary to highlight that all tests were performed at daytime and under good weather conditions, but other aspects that might affect the system performance were undetermined variables. These factors were related to the road marking pattern and discontinuity, color (white or yellow), visibility of road markings and some dust; some shadows over the carriageway; and sun glaring (E/W orientation). Some of these parameters are static and some others are dynamic, all requiring further research. In fact, the high concentration of 100% manual runs just before the automatic lane width threshold suggests that a static factor – such as road marking pattern, road marking width, etc. – has a synergic effect with the lane width.

CONCLUSIONS

As well as other road design features, lane width has been found to impact the disengagement probability of driving autonomation systems. The authors have explored how this factor affects the reliability of a level 2 vehicle throughout 81 lanes located at tangent sections of an urban arterial. Results show that lane width thresholds for human and automated lateral control can be clearly defined.

Three new lane width concepts are therefore proposed: **human lane width** – maximum width for which human is always requested for the steering control; **automatic lane width** – minimum width for which the steering control can always be performed autonomously; and the **critical lane width**, which presents the same probability of human and automatic lateral control.

For the tested system, human lane width was determined as 2.50 m, automated lane width was 2.75 m, while the critical lane width was established at 2.72 m. Note the very narrow range that shifts from complete manual to complete automated lateral control (0.25 m).

It is important to highlight that these thresholds were determined for a single LKA system. Other LKA/LCA systems are based on a variety of technologies and will present different limitations. The methodology proposed in this paper establishes a framework to test the capabilities of the different systems, without the need to know the underlying technology. Hence, this information could be used as a factor to define clear Operating Design Domains and therefore rapidly determine if any width-related disengagement is expected along a certain corridor.

In order to get some insight about the limitations of current marketed systems, a further research will include more observations with other makes and models, including heavy vehicles. These tests will be carried out in different Operating Design Domains and different geometries (such as horizontal and crest vertical curves), and different speeds. Adverse weather, night driving and sun glaring conditions should also be tested, to check how robust is a certain driving automation system technology to different ODD variations.

New parameters should also be considered in the future, such as the lateral position of the vehicle, to determine if it has some influence on the disengagement event. If so, it is expected a slight reduction of these thresholds, as well as a possible reduction of the range between manual and automatic lane widths. Every vehicle should be measured with and without mirrors, considering the outer boundary of the vehicle.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: A. García; data collection: A. García; analysis and interpretation of results: A. García and F.J. Camacho-Torregrosa; draft manuscript preparation: A. García and F.J. Camacho-Torregrosa. All authors reviewed the results and approved the final version of the manuscript.

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