EFFECT OF THE ROBUSTNESS LAYERS DEFINED BY EURO NCAP FOR THE NEW CRASH AVOIDANCE 2026 PROTOCOL ON PERCEPTION CAPABILITIES OF VEHICLE SENSORS

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ABSTRACT

This paper quantifies the impact of Euro NCAP 2026's 'robustness layers' on automotive sensor perception performance in ADAS object detection and tracking. The new standard introduces controlled variability in test scenarios to better reflect real-world conditions, encouraging development of ADAS (Advanced Driver Assistance Systems) that perform consistently on public roads as on test tracks. Understanding these effects is critical for designing reliable ADAS systems.

The study evaluates perception system performance under robustness layers versus standard scenarios, analyzing both perception-focused and control logic-focused layers from the Euro NCAP 2026 Crash Avoidance protocol. Evaluated layers include target parameters (speed, trajectory, acceleration, position offset) and environmental conditions (night, clutter) -specifically those testable on proving grounds. Data is collected using state-of-the-art automotive-grade sensors: a front long-range radar and front monocular camera with embedded perception, installed in standard vehicle positions. Object-level sensor data and ground truth are recorded during testing.

Performance evaluation focuses on object detection using KPIs including detection range, position, and velocity error. The study compares sensor performance with and without robustness layers and quantifies individual layer effects on performance degradation.

The study provides an objective assessment of sensor technical limitations against new robustness requirements. However, it focuses solely on perception; overall ADAS performance depends on both perception and control logic. Complete vehicle-level performance combines both factors, and performance reduction may stem from either source. This study addresses perception limitations specifically.

This work addresses a major industry challenge—closing the gap between standardized testing and real-world performance -aligning with advanced perception sensors and ADAS effectiveness research.

Keywords: ADAS, Robustness, Perception, Sensors, Radar, Camera, Object detection, Euro NCAP, Testing

INTRODUCTION

The European New Car Assessment Programme (Euro NCAP) [1] provides independent, objective safety ratings through standardized testing. It informs consumers and incentivizes manufacturers to design safer vehicles in pursuit of higher ratings. However, a system that performs well under controlled, favorable conditions might underperform in the real world under more challenging conditions. For example, a vehicle tested during the day might report a high score, but the vehicle's performance might be significantly degraded in real-world night driving. This motivated the introduction of 'robustness layers' in the Euro NCAP 2026 Collision Avoidance protocol [2], to account for real-world variability and improve score representativeness. This protocol groups test scenarios into two main categories: the Standard Range, which represent the traditional testing conducted on proving grounds with very accurate control parameters, and the Robustness Layers, which are designed to test systems under more diverse conditions to model real-world variability.

Performance Evaluation

Standard scenarios (standard range)

The Standard Range refers to the most basic and controlled format of a test scenario, representing fundamental performance expectations. Scoring in the Standard Range is calculated by assigning a sub-score to each "matrix cell" (combination of speeds and impact locations) according to the manufacturer's predicted performance. The result is the normalization of these sub-scores relative to the total score available for that range. To verify the predicted performance, a number of verification tests are randomly selected.

Evaluation under robustness layers

Robustness layers introduce complexity and variation to challenge vehicle systems, seeking reliable performance in the "real world." The layers are divided into two categories: **Perception** (focused on detection system robustness, what the vehicle is able to detect) and **Decision and Control** (focused on control logic, how the vehicle decides to react).

Analysis of Robustness Layers

The main difference in evaluation lies in whether a physical verification test of the layer is required: Decision and Control layers generally require verification testing on proving grounds, while Perception layers are often demonstrated through field data on public roads.

Layers Focused on Perception. These layers mostly seek to demonstrate system functionality in the presence of variable environmental or target conditions, which directly challenge the vehicle's sensors and perception processing.

- **Target Type/Appearance:** Detection of different types of collision opponents (e.g., N1, N2, N3 category vehicles) or the same type but with different appearance (e.g., color, shape)
- **Adverse Environmental Conditions:** Function availability in the presence of rain, fog, dirt, ice or humidity.
- **Lighting and Clutter:** Performance in darkness (1 lux), under sun glare or headlight glare. Also includes performance in environments with infrastructure/clutter (objects such as traffic signs, or stationary pedestrians).

Layers Focused on Control Logic (Decision & Control). These layers mostly evaluate how the system reacts to small variations in test parameters or the presence of driver inputs before collision.

- **Driver input pre-crash:** Normal driving without steering robot or speed control, replicating naturalistic human behavior
- **Target Parameter Variation:** Speed, Acceleration, Initial Position, Trajectory/Heading. Small variations in nominal target speed, acceleration or initial position

In summary, while standard scenarios establish the performance baseline under controlled conditions, robustness evaluation delves deeper into system reliability. Decision and Control layers require that performance under varied conditions (e.g., driver inputs or small trajectory deviation) does not degrade compared to the standard; Perception layers focus on demonstrating that the system is robust and functional under complex real-world conditions, often using field data for validation. In the following section, the methodology for the analysis is described.

This paper focuses on proving ground testable layers, quantifying their effect on system perception capabilities. It shall be desirable that layers focused on control logic present limited effect, while layers focused on perception show larger degradation. It is also aimed under the scope of this paper to understand whether these new robustness requirements are reachable using current sensor capabilities.

METHODOLOGY

The methodology used in this analysis consists of experimental testing on proving grounds with state-of-the-art sensors against a reference, evaluated under standard and robustness layers and assessed against relevant perception metrics.

Sensors

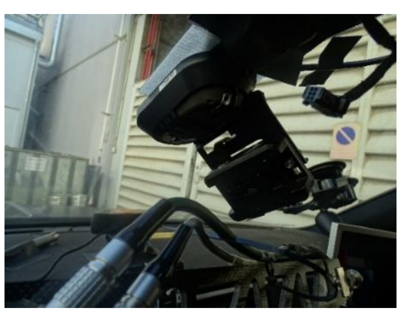
The first relevant step in the process is sensor selection. Two sensor types were chosen, one monocular camera sensor and a long-range radar sensor. As the objective of the study is to understand potential issues of production ADAS with the new robustness requirements, state-of-the-art automotive-grade sensors are used.

The selected camera sensor has an angle view range of 52º in horizontal component and 42º in vertical. It includes the latest iteration of state-of-the-art in machine vision software. This unit includes the object data publication option via CAN bus and provides an accessible software interface to calibrate the camera sensor properly.

The radar unit is an automotive production series and is designed to be used for general purpose applications. It also has a CAN bus interface and provides information in the form of clusters or objects detected depending on the configuration. It has a +/-9º FOV beam for far range (250 m distance) with an accuracy of +/-0.4 m and +/-60º for near range (20 m distance) with an accuracy of +/-0.10 m.

Once the sensors have been defined, they are mounted on a test vehicle (here in after, Vehicle Under Test, VUT). A 4-door saloon was selected as a VUT. Both were installed in regular positions of automotive applications. The camera sensor was installed in the center of the windshield, as shown in Figure 1. A customized metal structure was made to hold the radar unit in the front grill, with the proper wiring of the CAN bus and power supply, as shown in Figure 2.

Sensors were calibrated according to the manufacturer's specifications. During the process, no evidence of mis-mounting or misalignment was found. Calibration errors were minimum.



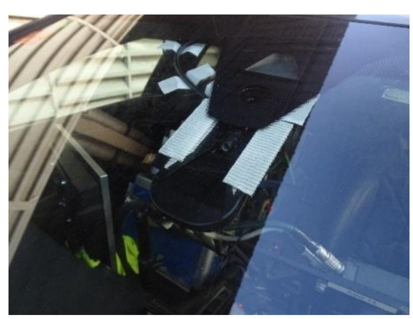


Figure 1. Camera sensor installed on the windshield.

Figure 2. Radar sensor installed in the VUT front grill

Test Instrumentation

The VUT (Vehicle Under Test) was instrumented with driving robots, shown in Figure 3, in order to perform the physical tests with controlled trajectories and reference. Vehicle motion is provided by a differential Global Navigation Satellite System (dGNSS) with Real-Time Kinematic positioning (RTK) and an inertial unit with less than 2 cm accuracy. This setup is the standard proposed under Euro NCAP testing for crash avoidance. The data acquisition system, shown in Figure 4, is composed of a rugged automotive PC, using Vector Informatik devices to record all the information coming from the CAN buses from the sensors. Data synchronization is ensured by these Vector devices.

Figure 3. Driving Robot

Figure 4. Data acquisition system

For data monitoring and recording purposes, the software used was Vector CANape v21, with Option Driver Assistance. The software, displayed in Figure 5, is capable of parsing, displaying and recording the objects detected for each sensor, including the reference GPS sensor device.

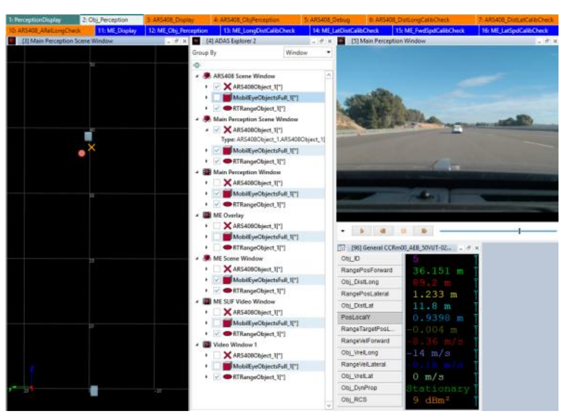


Figure 5. Data Measurement and recording software

Data Analysis

Data analysis follows the methodology described in [3]. For each test run and sensor, a matrix is built with the following columns: timestamp, object id, x (longitudinal relative position), y (lateral relative position) v_x (longitudinal relative speed), v_y (lateral relative speed). Then for each sensor cycle, one row per detection, or a row with only the timestamps if there are no detections, is added.

The same matrix is built for the reference sensor, based on two connected dGNSS with RTK that provide the relative position of the target with an accuracy of 2 cm.

Then, timestamps are interpolated on the reference matrix to match the timestamps on the sensor matrix and for each timestamp in the sensor matrix. Only the closest detection to the ground truth target in Euclidean distance (x,y) is kept. If this Euclidean distance is larger than 5 m and 15% of the real distance to the target from the reference matrix, the detection is discarded. These values are selected empirically, in order to consider only detections that correspond to the target.

Then, errors in x, y, v_x, v_y are calculated and added to the sensor matrix, along with the reference longitudinal position, *ref_x*. For each test, e.g. CCRs_AEB_80VUT_50, these errors are plotted with respect to *ref_x*, aggregating all repetitions and calculating the mean and standard deviation in 1 m distance bins, as seen in Figure 6 and Figure 7.

The results from different tests can be shown together, aggregating results in 10 m distance bins from 0-10 m to 140-150 m, and the detection rate can also be calculated across those same distance bins as the ratio of number of instants where the sensor detects the target over the number of instants where the sensor produces an output. An exemplary result can be seen in Figure 10.

Lastly, results are aggregated across all test groups under the same robustness layer, and corresponding standard tests and results are grouped in 50 m bins, from 0-50 m to 100-150 m. This provides a summary comparison of the performance of the sensor under standard conditions and with the robustness layers, as seen in Figure 8 and Figure 9.

Test Matrix

The procedure indicated in chapter 5.2.1 of Euro NCAP Frontal Collisions protocol [2] version has been followed for the definition of the test matrix of this study. The tests performed were focused on AEBC (Autonomous Emergency Braking in Car oponent scenarios) test protocol. The layers applied and the corresponding testing parameters are listed in Table 1.:

Table 1. Tests executed

Type	Robustness Layer	CCRs	CCRm	CCRb	CCFhos	CCFhol	CCFtap	CCCscp
TARGET	Speed				80 km/h-50% 40 km/h-75%	80 km/h-50% 40 km/h-75%	10km/h vs 30km/h 20km/h vs 60km/h	40km/h vs 40km/h 20km/h vs 40km/h
	Acceleration			80 km/h-50% 50 km/h-0%				
	Initial Positon offset			80 km/h-50% 50 km/h-0%			10km/h vs 30km/h 20km/h vs 60km/h	
	Trajectory/Heading	80 km/h-50% 50 km/h-0%						
	Type	FOT	FOT	FOT	FOT	FOT	FOT	FOT
	Appearance	FOT	FOT	FOT	FOT	FOT	FOT	FOT
ENVIRONMENT	AWC	FOT	FOT	FOT	FOT	FOT	FOT	FOT
	Illumination (Night)	80 km/h-50% 50 km/h-0%	80 km/h-50% 50 km/h-0%	80 km/h-50% 50 km/h-0%	80 km/h-50% 40 km/h-75%	80 km/h-50% 40 km/h-75%	10km/h vs 30km/h 20km/h vs 60km/h	40km/h vs 40km/h 20km/h vs 40km/h
	Illumination (Glare)	FOT	FOT	FOT	FOT	FOT	FOT	FOT
	Infrastructure / Clutter	80 km/h-50% 50 km/h-0%	80 km/h-50% 50 km/h-0%	80 km/h-50% 50 km/h-0%				40km/h vs 40km/h 20km/h vs 40km/h
	Obscuration / Obstruction							

The tests marked as FOT (Field Operational Tests) have not been tested, as they are evaluated during public road driving under non-controlled environments.

RESULTS

In this section, the main results where differences can be observed are reported.

For the radar, a significant difference in lateral position in a CCRs-Heading, and small differences in longitudinal error for CCRs-Clutter, CCFtap-Speed, and CCFhos-Speed are reported in Figure 6 and Figure 7.

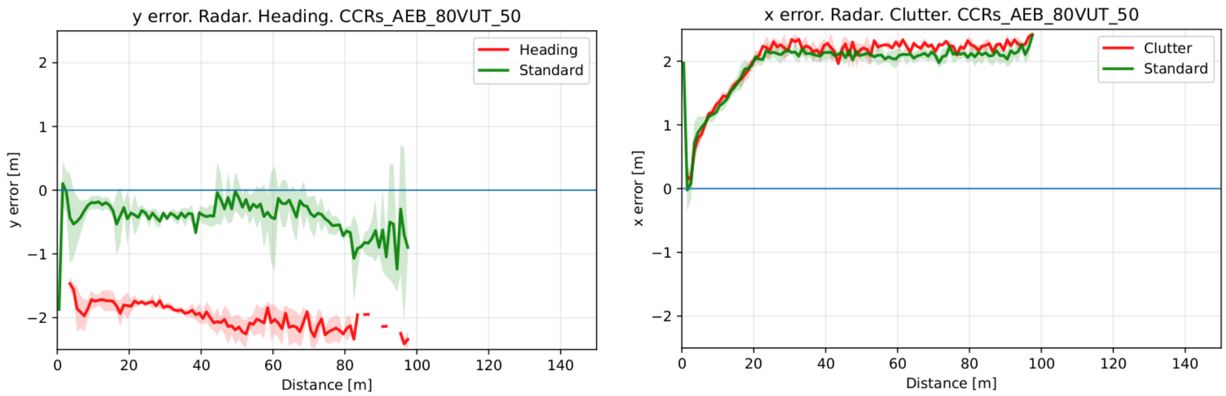


Figure 6. Radar. Left: Lateral error, heading vs standard. Right: Longitudinal error, clutter vs standard. The mean (main line) and the standard deviation (shadowed areas correspond to +- 1 std) are reported.

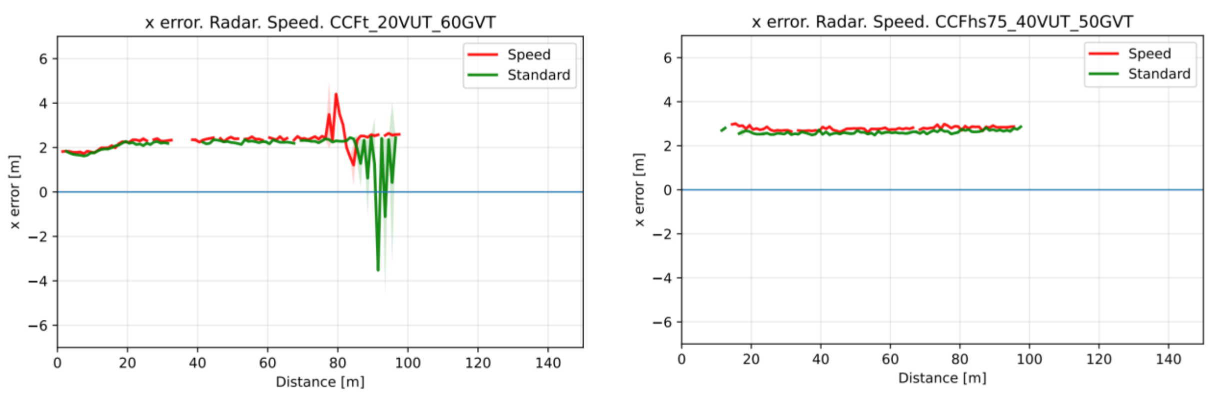


Figure 7. Radar. Left: Longitudinal error, speed vs standard. Right: Longitudinal error, speed vs standard. The mean (main line) and the standard deviation (shadowed areas correspond to +- 1 std) are reported.

The camera sensor is much more affected, as it can be seen in Figure 8 and Figure 9, reporting the overall difference in perfomance across test of the robustness layers Illumination and Heading, compared to standard.

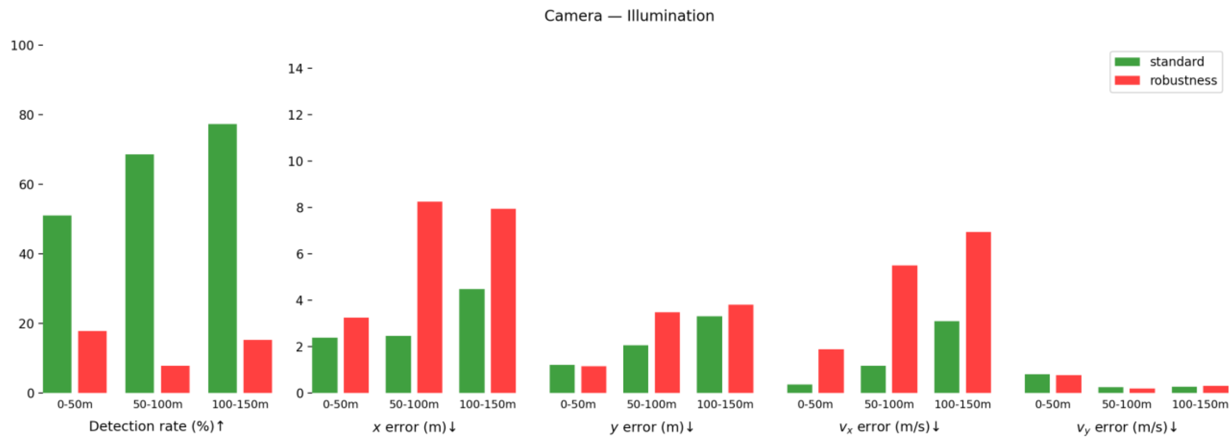


Figure 8. Detection rate and error for the camera. Standard vs Illumination.

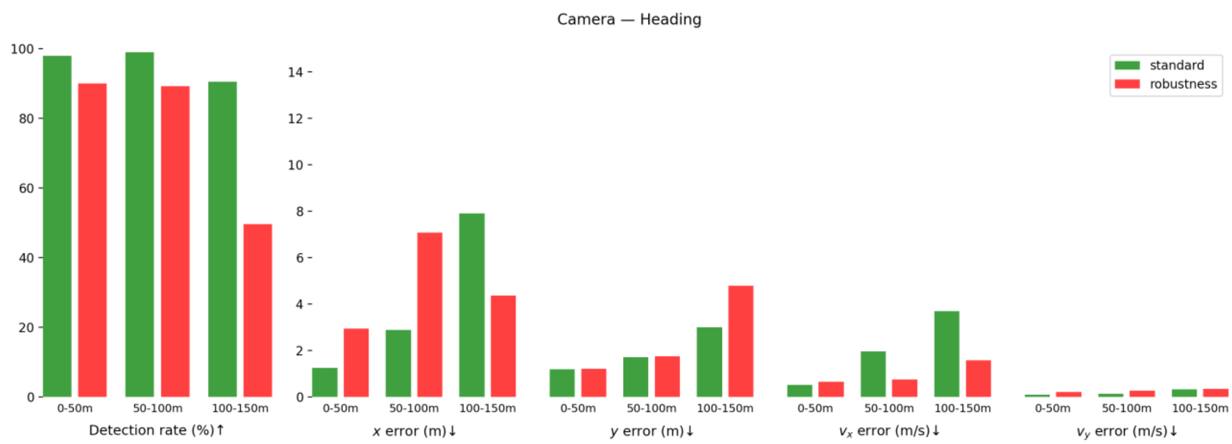


Figure 9. Detection rate and error for the camera. Standard vs Heading.

For additional details on the effect in each test of the Illumination robustness layer, the detection rate across tests comparing standard and Illumination tests is reported in Figure 10.

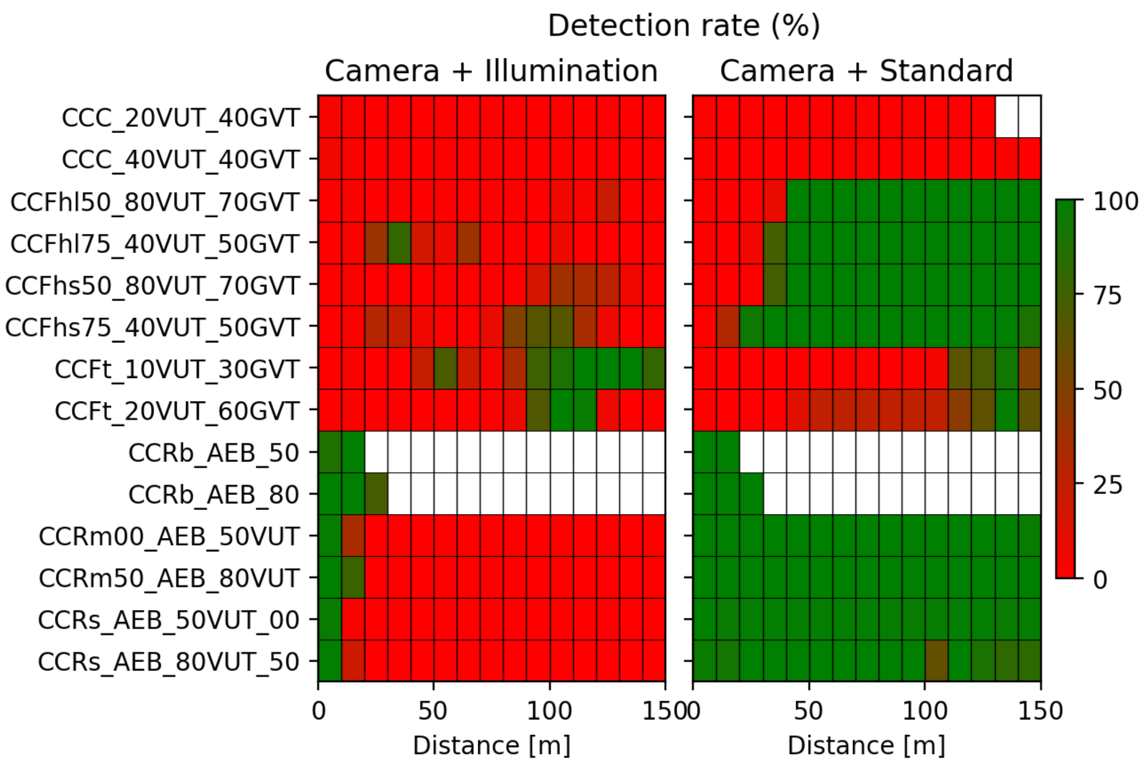


Figure 10. Detection rate at 10m distance bins for each test type. Standard vs Illumination.

Overall, the result of the performance for each sensor and robustness layer is summarized in Table 2, where green represents the sensor performing equally in standard and with the robustness layer, yellow represents and observable difference in performance between standard and with the robustness layer, and red means the performance is clearly degraded when testing with the robustness layer compared to standard.

Table 2. Summary of the effect of robustness layers compared to standard

Robustness Layer Category	Robustness Layer Target Parameter	Euro NCAP AEBC Scenarios													
		Radar							Camera						
		CCRs	CCRm	CCRb	CCFhos	CCFhol	CCFtap	CCCscp	CCRs	CCRm	CCRb	CCFhos	CCFhol	CCFtap	CCCscp
Target Actor	Speed														
	Acceleration														
	Initial Position														
	Trajectory/Heading														
Environment	Illumination														
	Infrastructure/Clutter														

No observable difference · Observable difference · Robustness degrades performance significantly · GVT not detected by the sensor · Not performed

DISCUSSION

Based on the results described in the previous section, cameras are greatly affected by the Illumination robustness layer, especially in terms of detection rate and longitudinal accuracy, both in positioning and velocity, as shown in Figure 8 and Figure 10. Cameras are affected by the Heading robustness layer, in terms of detection rate for long-range objects (100-150m), and in terms of longitudinal error for near and medium objects (0-100 m), as shown in Figure 9. Other robustness layers do not lead to a significant performance degradation on the camera.

Radars are not significantly affected by the robustness layers, but in some concrete tests, a robustness layer slightly affects the performance of the radar, as seen in Figure 6 and Figure 7.

Regarding the CCCscp (Car to Car Crossing) scenario, in most of the tests performed, neither the camera nor the radar are able to detect the target soon enough to get useful information to judge the effect of the robustness layer. The radar unit is mounted on the front grill. Therefore, without the use of corner radars this scenario is really difficult for the sensor due to the setup used. Similarly, the camera used in this study as a limited field of view and is not designed to detect crossing objects.

These experimental findings are aligned with the theoretical expectations considering the physics of each sensor, and previous literature [4-8]. Cameras, being passive sensors working on the visible spectrum, rely on ambient illumination and more challenging lighting conditions such as night conditions affect it greatly [4-7]. In contrast, radars are active sensors operating in millimeter-wave frequency bands (76-81GHz), therefore changes in visible light (400-790THz) do not affect it [8].

Within the initial concept for robustness, the Layers Focused on Control Logic (Decision & Control) are not intended to affect sensor perception performance. The test results in this study show that some of the target parameter variations present a limited performance drop both for camera and rada. This finding suggests that overall robustness performance cannot totally be decoupled in perception and control logic. And this means that target parameter variations have to be sorted out considering sensor limitations (results in this study) and control logic tuning (final goal with robustness evaluation for these layers). Anyhow, as Euro NCAP evaluation is done at complete vehicle level, without differentiating perception and control logic, this is not expected to have any impact in the assessment.

LIMITATIONS

The study is focused on the evaluation of the effect of Euro NCAP's 2026 robustness layers on automotive-grade sensors using 2 widely used sensors as representatives, one monocular camera and one radar.

The analysis is limited to proving ground testing, and the robustness layers intended for field operational tests are therefore out of the scope of this work and left for future work. Moreover, since this study focuses on the effect on perception, one should be careful when extending the conclusions of this work to full vehicle testing.

The layer for Target Type and Appearance has not been evaluated in this study. The reason is that, while it is a layer intended for perception, it is very difficult to evaluate it objectively in proving grounds. Radars and cameras perception is trained to recognize real targets (real pedestrians, real cyclists, real cars…), but in proving grounds artificial targets are used. The test protocol [2] defines standardized targets (pedestrian targets, cyclist targets, car targets…) that have proper reflectivity and conspicuity characteristics that sensors can perceive. The limitation for type and appearance variations is that it cannot be guaranteed that the sensors would keep classifying these target changes into real targets.

CONCLUSIONS

The Illumination robustness layer is clearly the robustness layer that has a larger impact on perception from the Euro NCAP 2026 robustness layers intended for proving ground testing. The camera has a very significant performance degradation at night, therefore these new robustness layers will encourage carmakers as well as automotive camera suppliers to improve their systems and aim to have a consistent performance across day times and illumination levels. Other cameras such as event cameras [9] or gated cameras [10] are significantly less impacted by low illumination environments, however their use in an automotive context is currently mainly academic.

Some layers for Target Parameter Variations have shown impacts in sensor performance. The differences are observable but limited. It is expected that the fusion of different sensors (usually radar and camera, which have complementary capabilities) with the convenient calibration of the control logic can overcome this minor limitation.

The other robustness layers might affect ADAS functions due to other components being affected, but this study shows that they do not have a significant impact on perception performance.

Overall, the results suggest that the new robustness requirement defined by Euro NCAP can mostly be addressed by additional efforts in control logic calibration which usually is one-time cost during development, rather than by the use of more accurate sensors, which is usually a unitary cost for every vehicle manufactured.

Most of the robustness layers targeting perception are intended for field operation tests. Therefore, future work analyzing whether the appearance and weather conditions affect the performance of automotive sensors would be highly valuable to complement this study. Previous literature [11-15] on the effect of appearance and weather conditions in perception suggests that the robustness layers to be tested with field data will have a significant impact on perception performance.

DISCLAIMER

All tests were conducted on the same proving grounds with the same tools and applying the same analysis criteria. The results presented correspond to the performance of the samples used during the tests. Individual performance might be affected by uncontrolled factors and overall performance is limited to the representativity of the number of tests and scenarios.

ACKNOWLEDGMENTS

The authors gratefully acknowledge Euro NCAP. Euro NCAP leads the development of new test procedures for ADAS in general and has defined and included the concept of robustness in the new assessment. This will have a positive impact in a more accurate evaluation of safer vehicles. Also it is important to acknowledge the contribution of all participants in the Euro NCAP WG for Crash Avoidance where the concept of robustness has been defined, including Euro NCAP members, test laboratories and automotive industry participants.

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