Robustness Testing of CNN-based Traffic Sign Detection using a Simulation Environment

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***Abstract*—This work presents a method using the dSPACE simulator to assess the robustness of neural networks for vision-based autonomous driving. The approach is applied to a case study on traffic sign detection in adverse weather conditions.**

***Index Terms*—Traffic sign classification, image classification robustness, vehicle simulation, autonomous driving systems.**

I. Introduction

Traffic sign detection [1] is a core perception task in Autonomous Driving Assistance Systems (ADAS) and intelligent transportation applications. This ADAS feature uses a camera mounted on the car's windshield and machine learning to scan the road for traffic signs. Although modern classifiers can achieve high accuracy under standard conditions, their performance may degrade substantially in the presence of adverse visual factors such as rain, low illumination, fog, and snow [2]. Neural network-based perception and decision-making procedures for object detection are susceptible to image perturbations. This work proposes a simulation-driven approach that uses dSPACE to generate synthetic driving scenarios in which an ego car drives under controlled adverse weather conditions. As the simulation evolves, the virtual camera generates new frames that are passed to a Python script that invokes the classifier.

The main advantage of the proposed approach is the ability to systematically control many parameters of the scenario, in particular the severity of weather conditions, thereby enabling a fine-grained assessment of the robustness of the detection procedure, while exploiting the straightforward integration between dSPACE and Python. The long-term goal is not merely to use simulation as a benchmarking platform, but also to exploit it as a targeted source of additional training data to enhance detection robustness.

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II. Background

A. dSPACE

dSPACE[1] provides a state-of-the-art integrated simulation and testing environment for the development and validation of automotive systems, including ADAS and automated-driving functions. The testing framework used in this work is based on a dSPACE toolchain, mainly composed of three modules: ASM, AURELION, and ControlDesk. ASM is a series of complex Simulink models that can be parametrized to define the virtual driving scenarios, including road layout, ego-vehicle trajectory, and traffic-sign placement. AURELION provides the sensor-realistic rendering of the scenario, generating the camera data used as input for the YOLO-based detector under different environmental and visibility conditions. ControlDesk is used to execute and monitor the experiment, record relevant signals, and support data collection for the subsequent evaluation. Together, these tools enable repeatable testing of the same road-sign detection scenario while systematically varying weather, illumination, camera quality, and visibility conditions.

B. Road sign classifier

The classifier used in this work is trained on the images of the Austrian Highway Traffic Sign Data Set (ATSD) introduced by [3], a real-world benchmark for traffic sign detection and classification on highways. The dataset was derived from HD video recordings and contains 7454 high-resolution RGB traffic-scene images with 27,521 traffic-sign annotations, together with 20,683 cropped sign patches for classification. Among these sign patches, 13,261 are prohibitory signs, including speed limits ranging from 30 km/h to 130 km/h. The baseline recognition model for this ATSD uses a two-stage detection-and-classification pipeline. The first stage aims to detect a sign in the scene with a YOLO4-tiny architecture, the second one identifies it with a CNN [4].

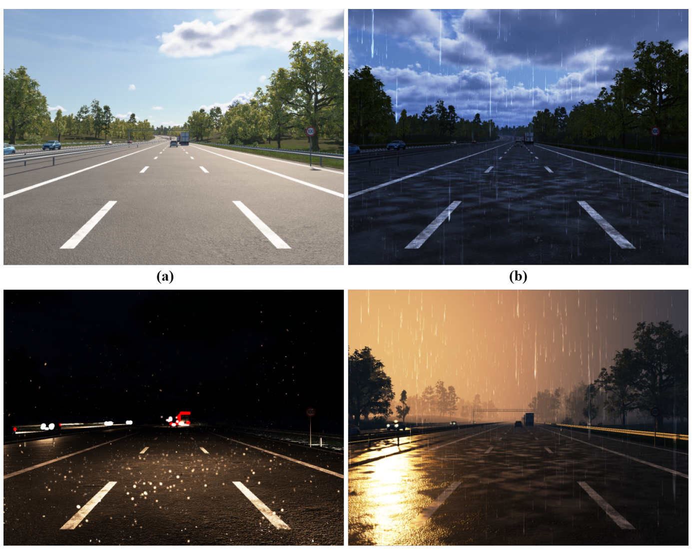
[1] https://www.dspace.com/

III. Experimental Setup

The testing campaign is conducted in a dSPACE simulation environment using a mixture of virtual scenarios, encompassing highway, urban, and country roads. Each scenario includes a sequence of traffic signs placed along the road, with the ego vehicle following a predefined trajectory and a speed profile coherent with the speed limits dictated by the signs. The use of simulation allows the same road layout, vehicle path, and sign placement to be preserved while varying environmental and visibility conditions in a controlled way.

The scenario specification is inspired by Commission Delegated Regulation (EU) 2021/1958[2]. In particular, the regulation is used as a reference for selecting relevant road-sign categories and defining meaningful test situations for Intelligent Speed Assistance-related perception.

The operational conditions considered include normal weather, fog, rain, snow, camera degradation, and diverse illumination levels (see Fig. 1). These conditions are selected because they represent common factors that can reduce the reliability of camera-based perception systems.



(a) (b) (c) (d)

Fig. 1. Example of a road sign rendered under increasingly challenging weather and illumination conditions: (a) daytime with clear sky, (b) daytime with clouds and rain, (c) nighttime with light snow, and (d) dawn with heavy rain and fog.

Performance is evaluated using two complementary metrics. The first is mAP@50, (Mean Average Precision at intersection over union threshold of 0.5), which provides a standard measure of detection quality and enables comparison with previous object-detection studies. The second is the distance to the sign at first stable detection, converted into time under the assumption of constant vehicle velocity. To avoid counting isolated or spurious detections, a sign is considered detected only when it is correctly identified for three consecutive frames. We denote this metric FSDTD@3, for First Stable Detection Temporal Distance at three frames. FSDTD@3 is intended to capture the operational relevance of detection timing: a sign detected late may still contribute positively to mAP, but may not provide sufficient time for a downstream driving function to react.

[2]https://eur-lex.europa.eu/eli/reg_del/2021/1958/oj/eng

IV. Preliminary Results

Preliminary experiments were conducted on a 2.3 km roadway scenario. Traffic signs were placed approximately every 350 m, following the principle of avoiding multiple signs being simultaneously visible in the system's field of view, as indicated in the 2021/1958 regulation. The ego vehicle speed profile was defined accordingly. Frames were captured and fed to the Python script every 40 ms. Multiple simulation runs were then performed by varying weather and illumination conditions in a controlled manner, while keeping the remaining scenario elements unchanged. Table 1 reports the mAP@50 under the four weather and illumination conditions shown in Fig. 1, and the FSDTD@3 values for the first sign expressed in seconds.

TABLE I
mAP@50 under different weather and illumination conditions, and FSDTD@3 for the first traffic sign.

Case	Weather	Illumination	FSDTD@3	mAP@50
(a)	Clear sky	Daytime	3.529	88.4
(b)	Clouds and rain	Daytime	3.402	66.1
(c)	Light snow	Nighttime	1.819	27.3
(d)	Heavy rain & fog	Dawn	1.523	29.5

These preliminary results indicate that increasingly adverse weather and illumination conditions tend to reduce the first stable detection distance, potentially limiting the time available for downstream vehicle functions to react.

V. Conclusions

This study reports some preliminary results of an ongoing research activity aimed at defining a methodology to systematically evaluate the robustness of an ML-based system for road sign recognition. The methodology starts with the requirements set out in the Commission Delegated Regulation (EU) 2021/1958. To demonstrate the effectiveness of the proposed methodology, we are setting up a series of additional simulated runs in the dSPACE driving simulation environment.

References

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