Measuring the effects of environmental influences on Object Detection

1st Niklas Bunzel
Fraunhofer SIT / ATHENE / TU Darmstadt
Darmstadt, Germany
bunzel@sit.fraunhofer.de

2nd Michel Geißler
TU Darmstadt
Darmstadt, Germany
michel-geissler@web.de

3rd Gerrit Klause
Fraunhofer SIT / ATHENE
Darmstadt, Germany
gerrit.klause@sit.fraunhofer.de

***Abstract*—Object detection is a complex task that faces many challenges, especially those related to environmental influences. Although studies have examined the effect of rain on object detection, few have analyzed other adverse weather conditions like snow, fog, and wind and varying levels of intensity. Existing object detection benchmark datasets fail to provide labeled intensities of weather conditions, limiting robustness assessment and cross-study comparisons. This study uses a 3D Unity simulation to evaluate object detection algorithms under different weather conditions to improve the understanding and design of robust systems for real-world applications.**

***Index Terms*—Object detection, Environment, 3D, Robustness**

I. Introduction

Object detection is increasingly used in everyday life and especially in industry applications. Even though many approaches are able to achieve high accuracies in the detection of objects, they are prone to errors in adverse environmental conditions. This is problematic in many application areas, such as autonomous driving [1], facial recognition [2], agriculture [3], sports or industry [4]. In cases where object detection is performed outdoors, environmental conditions can influence object detection performance. This influence has hardly been studied at all [5] and if so, mostly for rain [5], [6], [7], [8]. In addition, only few of the papers use meterological intensity levels in the study, limiting comparability between papers and real-world utility.

In this paper, object detection algorithms will therefore be evaluated under different environmental conditions, camera effects and intensity levels to determine the influence of each condition on object detection. Thereby, environmental conditions or certain parameters can be identified which make the detection of objects in the image impossible or difficult.

In order to systematically investigate the environmental influences and camera effects on object detection, a simulated 3D environment has been implemented in Unity. The 3D simulation allows to simulate different environmental conditions like rain, snow or fog in different meterological intensity levels and to generate synthetic image data sets for training and evaluation. Using simulated 3D data for training AI-models and applying them on data in the wild has proven to be successful as shown by the work of [9].

II. Simulation

The simulation in this paper consists of twelve main objects placed in a landscape that is as realistic as possible. Each of these main objects is surrounded by 6 cameras pointing at the object from different perspectives. This allows 72 images to be created simultaneously. In order for the images to represent realistic scenes, numerous other objects were placed next to the main objects. In order to capture images in different environmental conditions, a weather simulation is integrated with different weather types and intensity levels.

a) Rain: Rain is precipitation in liquid form formed in clouds by condensation [10]. In this paper, rain intensity is expressed in $[l/m^2]$ per hour and is modeled using specific measurements for raindrop size, density, and speed to calculate rain intensity and simulate realistic precipitation effects.

b) Snow: Snow is precipitation in solid form that forms in clouds. Snowfall intensity is expressed in l/h or mm/h. This study models snowfall, detailing snowflake size, speed, and density to calculate snowfall intensity and realistically represent snow in various conditions.

c) Fog: Fog is defined as very small water droplets in the air near the ground, formed by condensed water vapor. We speak of fog when the visibility is less than 1000m. This study combines linear and volumetric fog to realistically simulate, depict and adjust visibility conditions, exploring its impact on object detection.

d) Wind: Wind is the directional movement of air particles in the atmosphere. Wind speed is used to describe wind intensity. This study uses realistic wind effects based on the Beaufort scale, affecting the movement of rain, snow, fog, and vegetation according to different wind intensities.

e) Camera Effects: Additionally three important camera effects are investigated, Motion Blur, Exposure Value and Depth of Field. The simulation of the effects is done with the postprocessing method provided by Unity.

III. Evaluation

We used our framework to generate various data sets with different environmental conditions. Additionally, to increase reliability, all data sets were generated multiple times and the mean and standard deviation for the mAPs (with an IoU threshold of 0.5) were calculated for each data set. We also evaluated the performance of YOLOv8 [11] and

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DETR [12]; however, their results were slightly worse compared to YOLOv5 and Faster R-CNN, which we believe is due to the difference in data distribution between 3D generated data and real-world data. Therefore, we decided to focus on the results for YOLOv5. We analyzed the mAP for YOLOv5 [13] and Faster R-CNN [14] for the different environmental conditions and used the default torchvision models of YOLOv5 and Faster R-CNN with pre-trained weights.

A. *Rain*

We examined the impact of rain on object detection algorithms Faster R-CNN and YOLOv5 through experiments involving various rain intensities and droplet sizes. Results indicated a decrease in mean Average Precision (mAP) with increasing rain intensity and droplet size, with larger droplets causing more significant degradation. YOLOv5 showed greater robustness to rain compared to Faster R-CNN. Additionally, raindrops on the camera lens also reduced mAP, though to a lesser extent than rain in the environment.

B. *Snow*

This study investigated the effects of snow through several experiments involving different intensities and conditions of snowfall and snow cover. Results demonstrated a progressive decrease in mean Average Precision (mAP) with increasing snowfall intensity, with YOLOv5 proving more robust than Faster R-CNN. Snow cover negatively impacted mAP, particularly under light snow conditions, though mAP stabilized with complete snow cover. This stabilization is possibly due to the reduced visibility of object edges against scattered or complete snow backgrounds. The combination of snowfall and snow cover resulted in the most significant mAP reduction, while snowflakes on the camera lens also modestly decreased mAP.

C. *Fog*

We assessed the impact of fog using experiments that involved linear fog at different intensities, combined linear and volumetric fog, and simulated fog on the camera lens. Findings showed that mAP remained stable under light to moderate linear fog but significantly decreased with dense fog, particularly when visibility dropped below 30 meters. Additional fog banks further negatively affected mA. YOLOv5 demonstrated greater robustness compared to Faster R-CNN in both linear and volumetric fog scenarios, showing a smaller reduction in mAP at reduced visibilities.

D. *Wind*

To investigate the influence of wind on Faster R-CNN and YOLOv5, different wind intensity levels were simulated. The results show that wind does not have a large effect on the mAP. Only very strong wind decreases the mAP by 3% for YOLO and 8% for Faster R-CNN.

E. *Weather Simulation Combinations*

We explored the effects of combined weather conditions on object detection algorithms.

Rain and Fog: : The combination of different intensities of rain and fog showed a progressive decrease in mAP as both intensified. Notably, the most significant reduction in mAP occurred at the lowest visibility levels in fog, where mAP dropped drastically, especially for YOLOv5. For rain, the largest decrease in mAP was observed at lower precipitation levels (0 to 30l/h), suggesting that mAP is more steadily affected by increasing rain than fog. Interestingly, the impact of fog on mAP appeared relatively independent of rain intensity.

Rain and Snow Cover: When rain was combined with snow cover, increasing rain intensity led to a successive decrease in mAP. The mAP decreased less significantly under conditions of high rain and dense snow cover. This might be because the color of the raindrops blends with the snow cover, lessening the visual disruption caused by rain, thus mitigating its negative impact on detection performance.

F. *Camera effect simulation*

This study examined camera effects on object detection: Exposure Value (EV) where EV -9 resulted in an mAP of 0, peaked at EV 0, then declined with overexposure and underexposure; Motion Blur demonstrated a decrease in mAP with increased speeds, notably more for YOLOv5, with Faster R-CNN showing greater robustness; and Depth of Field revealed a reduction in mAP as the f-value decreased, indicating challenges in object detection with a narrower sharp area in images.

IV. Conclusion & Future Work

The results indicate that environmental factors have varying impacts on object detection. Heavy fog has the most detrimental effect, significantly reducing detection performance. Light and medium linear fog have minimal impact, but dense fog banks gradually decrease detection performance. Increased distance between objects and the camera, as well as fogged camera lenses, also decrease performance. Heavy rain, with larger droplets, has the second largest negative impact on detection, reducing performance by an average of 42.5%. Detection worsens with higher rain intensity and larger droplets. Similarly, snowfall affects performance, but to a lesser extent than rain. Heavy snowfall and increased snow cover decrease detection performance. Wind has the least impact on object detection when the objects are static. Strong wind decreases the mAP by only 5.5% on average. For camera effects, motion blur has a greater impact than depth of field. Motion blur can reduce object recognition by up to 22%. Our findings highlight that current object detection algorithms have limitations under certain environmental conditions. YOLOv5 outperforms Faster R-CNN in most environmental conditions, demonstrating higher performance and robustness. In the future further influences on object detection should be considered like different cameras, lightning conditions and sun position, these can be integrated into our simulation. To make our simulated images look more real, we could adopt an image-to-image translation.

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References

[1] T. Ponn, T. Kröger, and F. Diermeyer, "Identification and explanation of challenging conditions for camera-based object detection of automated vehicles," *Sensors*, vol. 20, no. 13, p. 3699, 2020.

[2] L. Lang and W. Gu, "Study of face detection algorithm for real-time face detection system," in *2009 Second International Symposium on Electronic Commerce and Security*, vol. 2, 2009, pp. 129–132.

[3] O. Wosner, G. Farjon, and A. Bar-Hillel, "Object detection in agricultural contexts: A multiple resolution benchmark and comparison to human," *Computers and Electronics in Agriculture*, vol. 189, p. 106404, 2021.

[4] T. D'Angelo, M. Mendes, B. Keller, R. Ferreira, S. Delabrida, R. Rabelo, H. Azpurua, and A. Bianchi, "Deep learning-based object detection for digital inspection in the mining industry," in *2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA)*, 2019, pp. 633–640.

[5] M. Hnewa and H. Radha, "Object detection under rainy conditions for autonomous vehicles," *CoRR*, 2020.

[6] S. Hasirlioglu and A. Riener, "Challenges in object detection under rainy weather conditions," in *Intelligent Transport Systems, From Research and Development to the Market Uptake*. Springer International Publishing, 2019, pp. 53–65.

[7] S. Hasirlioglu, A. Kamann, I. Doric, and T. Brandmeier, "Test methodology for rain influence on automotive surround sensors," in *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2016, pp. 2242–2247.

[8] A. von Bernuth, G. Volk, and O. Bringmann, "Rendering physically correct raindrops on windshields for robustness verification of camera-based object recognition," in *2018 IEEE Intelligent Vehicles Symposium (IV)*, 2018, pp. 922–927.

[9] E. Wood, T. Baltrušaitis, C. Hewitt, S. Dziadzio, T. J. Cashman, and J. Shotton, "Fake it till you make it: Face analysis in the wild using synthetic data alone," in *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, October 2021, pp. 3681–3691.

[10] Deutscher Wetterdienst, "Wetter- und klimalexikon," 2022, [Online; accessed 14-3-2023]. [Online]. Available: https://www.dwd.de/DE/service/lexikon/lexikon_node.html

[11] Ultralytics, "Yolov8," 2023, [Online; accessed 05-1-2024]. [Online]. Available: https://github.com/ultralytics/ultralytics

[12] N. Carion, F. Massa, G. Synnaeve, N. Usunier, A. Kirillov, and S. Zagoruyko, "End-to-end object detection with transformers," in *Computer Vision - ECCV 2020 - 16th European Conference, Glasgow, UK, August 23-28, 2020, Proceedings, Part I*, ser. Lecture Notes in Computer Science, A. Vedaldi, H. Bischof, T. Brox, and J. Frahm, Eds., vol. 12346. Springer, 2020, pp. 213–229. [Online]. Available: https://doi.org/10.1007/978-3-030-58452-8_13

[13] "Yolov5 (6.0/6.1) brief summary," 2022, [Online; accessed 12.4-2023]. [Online]. Available: https://github.com/ultralytics/yolov5/issues/6998

[14] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," in *Advances in Neural Information Processing Systems (NIPS)*, 2015.