Provident Vehicle Detection at Night: The PVDN Dataset

Lars Ohnemus,1,*,† Lukas Ewecker,2† Ebubekir Asan,2† Stefan Roos,2 Simon Isele,2 Jakob Ketterer,1,* Leopold Müller,1,* and Sascha Saralajew,3,4,*†

1Karlsruhe Institute of Technology, Karlsruhe, Germany
2Dr. Ing. h.c. F. Porsche AG, Weissach, Germany
3Leibniz University Hannover, Institute of Product Development, Hannover, Germany
4Bosch Center for Artificial Intelligence, Renningen, Germany

{ohnemus.lars, sascha.saralajew}@gmail.com

Abstract

For advanced driver assistance systems, it is crucial to have information about oncoming vehicles as early as possible. At night, this task is especially difficult due to poor lighting conditions. For that, during nighttime, every vehicle uses headlamps to improve sight and therefore ensure safe driving. As humans, we intuitively assume oncoming vehicles before the vehicles are actually physically visible by detecting light reflections caused by their headlamps. In this paper, we present a novel dataset containing 59,746 annotated grayscale images out of 346 different scenes in a rural environment at night. In these images, all oncoming vehicles, their corresponding light objects (e.g., headlamps), and their respective light reflections (e.g., light reflections on guardrails) are labeled. This is accompanied by an in-depth analysis of the dataset characteristics. With that, we are providing the first open-source dataset with comprehensive ground truth data to enable research into new methods of detecting oncoming vehicles based on the light reflections they cause, long before they are directly visible. We consider this as an essential step to further close the performance gap between current advanced driver assistance systems and human behavior.

*The research was performed during employment at Dr. Ing. h.c. F. Porsche AG.
†Authors contributed equally.
1 Introduction

At night, provident perception of oncoming vehicles is essential for safe driving. The risk of fatal accidents is reduced by detecting oncoming vehicles early. Humans are capable of provident vehicle detection at night through predicting the position of other road users through their headlamps’ light glares and reflections long before the vehicles are directly visible. However, those light-artifacts are challenging to separate from other light sources within a typical rural scenery, so current vehicle detection systems only identify directly visible headlamps and do not take this natural human behavior into account. Besides diver assistance cameras, other sensor types commonly used for Advanced Driver Assistance Systems (ADAS), like LIDAR, are not even capable of detecting those features because those do not correlate to a physical object. Therefore, camera systems might be the only possible sensors appropriate to providently detect vehicles at night.

The provident detection of oncoming vehicles at night could be a key feature for new ADAS functionalities—for example, to predictively control the car’s high beam system before the oncoming vehicle is in direct sight. In addition to this obvious use-case, many other use-cases for such a provident detection system are possible. For example, at night, autonomous driving systems could use the information to reduce speed before tight bends or to notice other vehicles at intersections without direct visibility. Therefore, early detection could remove many causes of car accidents at night.

It may come to mind to use machine learning techniques to build a capable perception system for provident vehicle detection at night based on camera images. For this, convolutional neural networks and similar architectures have proven their superiority against other pattern recognition methodologies (e.g., Ren et al., 2015; He et al., 2016; Redmon et al., 2016). However, this superior performance comes at a price: A representative dataset for the task has to be recorded and evaluated. Any discrepancy between the acquired dataset and the application domain will be noticeable in the system’s real-world performance. This hurdle may not be too challenging for most tasks, but it is apparent for the described problem. At this point, no dataset for provident vehicle detection at night is publicly available. Even the representation and annotation method for light-features is up to debate. The task of predicting oncoming vehicles can be represented in various ways. For example, it is possible to assign each camera frame a label to describe whether a car is approaching. Phrasing the problem as a classification task does allow for a simple annotation but only a pure end-to-end approach, which is usually not suitable for ADAS since the system behavior would be not comprehensible. A more sophisticated way would be to apply commonly used object detection methods. In earlier work, we showed that bounding boxes around light-features can be used to train machine learning models (Oldenziel, Ohnemus, and Saralajew, 2020). But still, the problem of the end-to-end approach remains. Also, the description via bounding boxes is

---

1Light detection and ranging.
a non-intuitive restriction to the fuzzy nature of such light-artifacts.

Contributions

This work analyzes the problem of “provident detection of vehicles at night” and gives insights into the development process of a suitable dataset. The derived dataset is called “PVDN” (Provident Vehicle Detection at Night) and is designed in a way that allows the usage of various representation strategies. Three different representations are presented and discussed. To accelerate development, the PVDN dataset is made publicly available. Furthermore, source code is released to provide an easy interface to the dataset in Python and PyTorch.

Outline

The paper is structured as followed: First, a summary of related work is given. Building on the knowledge from previous work, a more general annotation strategy is presented. The strategy is then applied to a large number of preselected video sequences. Here, the annotation process is discussed, and the resulting PVDN dataset is analyzed. To conclude, the results as well as potential future concepts are discussed.

2 Related work

Besides the fact that almost every car manufacturer offers a camera-based perception system to perceive oncoming vehicles at night—for example, to control the car’s high beams—the problem to providently detect oncoming vehicles based on their emitted light is not studied. This might be caused by the state-of-the-art vehicle detection systems at night that are based on blob detection systems followed by blob pairing and classification (e.g., Jurić and Lončarić, 2014; López et al., 2008; Sevekar and Dhonde, 2016; Alcantarilla et al., 2014; Eum and Jung, 2013). Of course, these systems are impressively efficient in terms of computational requirements to detect headlamp blobs at night but also induce a significant restriction: The detection of blobs. Obviously, light reflections in the environment caused by oncoming vehicles cannot be sufficiently described by blobs.

In previous work (Oldenziel, Ohnemus, and Saralajew, 2020), we performed a test group study to specify the discrepancies between current ADAS and human provident behavior. Additionally, as a proof of concept, we showed that the provident detection of vehicles at night is possible when using modern machine learning techniques like an adapted Faster-RCNN (Ren et al., 2015) architecture.

https://www.kaggle.com/saralajew/provident-vehicle-detection-at-night-pvdn
https://github.com/larsUhne/pvdn
The PVDN dataset

The PVDN dataset is derived from a test group study that investigated humans’ provident vehicle detection capabilities and consists of annotated grayscale camera images. During the study, the onboard camera of the test car was used to capture grayscale images of two different exposure cycles. The resulting image cycles are called “day cycle” (short exposure) and “night cycle” (long exposure). Image sequences of scenes (available through the test group study) are selected according to the appearance of oncoming vehicles and padded to create parts without vehicles in them. Mostly, such sequences begin when there is no sign of an oncoming vehicle yet (no annotation) and end when the vehicle has passed.

The main objective of this dataset is to divide the complex task of predicting vehicle positions at night without direct sight into single subtasks. Similar to human behavior, these subtasks consist of perceiving light-artifacts and predicting the position or occurrence of an oncoming vehicle. Therefore, we aim to design a dataset that provides rich information about features that we humans would use to detect oncoming vehicles at night. In the following, we describe in more detail how the dataset was derived and how the images of the scenes are annotated.

3.1 Terminology

A few definitions for clarification:

Scene A scene is a sequence of image frames. In each sequence, at least one oncoming vehicle can be found. All scenes were created from captured video frames obtained during the test group study.

Direct / indirect A vehicle is considered directly visible, when its headlamps are visible. Vehicles where only glares or reflections indicate its position are considered indirect.

Instance All spatially bound light artifacts (e.g., reflections, glares, or direct headlamps) are called “instance” of a certain vehicle.

3.2 Hierarchy

The information we want to retrieve from the raw image data spans multiple hierarchical levels. On the highest semantic level, the aim is to predict oncoming vehicles. To maintain generality, we assume that each scene may contain multiple vehicles. For each frame, the position of the vehicles needs to be specified. At this frame-level, the vehicles are detected without the time-coherence derived from a complete scene inspection. Since the vehicle position itself is an abstract notion for not directly visible vehicles, it can sometimes only be perceived through light artifacts within a frame. Those instances build up the knowledge about the vehicle and are therefore placed on the lowest semantic level. Figure 1 shows the relationship between those different entities. It should
be noted that valuable information could be lost if only the vehicle position is annotated.

The proposed hierarchy yields two requirements for a suitable dataset:

1. Both the vehicle position and the related instances need to be annotated, and
2. the annotations should be coherent over multiple frames to capture the temporal characteristics of an oncoming vehicle.

### 3.3 Vehicle Position

The annotation of an approaching vehicle poses two challenges:

1. How to represent the actual position within a frame, and
2. where to place the vehicle position when it is not visible yet.

In the first case, the most efficient way to annotate the position is to place a keypoint at a remarkable point on the vehicle. We used a keypoint placed on the road centrally between both headlights (e.g., Figure 2a). The actual size of the vehicle would be redundant information since it can always be inferred from the vehicle position and the two headlight instances. Stringently, in the second case, the position of indirect vehicle positions is annotated with a keypoint as well (see Figure 2b). So if the vehicle itself is not visible, the keypoint is placed at that point on the visible road, at which the vehicle will appear first. If the road touches the edge of the image, the intersection point is used. This approach has some key advantages:
Figure 2: Annotation examples: 2a shows an annotation of a direct vehicle position. 2b shows an indirect instance (glare) and a indirect vehicle position as well as an automatically inferred bounding box.
• It conserves temporal coherence when transitioning between indirect and
direct vehicle positions, and

• the keypoint can be directly used as a target when predicting the occur-
rence position of vehicles.

Additionally, a Boolean label is added to each vehicle position to specify whether it is direct or indirect.

3.4 Instances
To retrieve the maximal information content within a frame, light-artifacts are
annotated as well. In addition to the challenges for vehicle positions, the fuzzy
nature of the light-artifacts needs further thought. While direct instances are
well specified (headlights), the total number and size of the indirect instances
cannot be specified objectively. Therefore, we introduce the concept of salient
keypoints. For each spatially bound light-artifact, the intensity maximum is
annotated with a keypoint. This correlates nicely with the human perception,
looking around in the scene to find salient areas. So the keypoints put onto
indirect instances can be viewed as carefully selected eye-fixation points. While
this cannot be seen as absolute ground truth, it still gives hints towards the
attention of human annotators. These keypoints can be used to derive more
general and objective representations than, for example, hand-drawn bounding
boxes. Also, for direct instances this annotation strategy translates nicely since
the keypoint can be placed centrally within the headlight cone. Additionally, a
Boolean label is added to each instance keypoint to specify whether it is direct
or indirect.

3.5 Annotations methodology
As already mentioned, the annotation of indirect instances and vehicle positions
is subjective. To minimize the subjectiveness effects, an iterative procedure for
the annotation process was chosen. Keypoints for vehicle position and instances
were annotated with a custom annotation tool. Then, the annotations were
reviewed by multiple annotators and the placement and number of keypoints
was discussed. Additionally, a set of guidelines for different conditions and cir-
cumstances was given to the annotators. The reviewed annotations were then
corrected by an annotator. An additional comment feature within the annotation
tool ensures ease of communication. Simple replacement patterns are used
as well to unify different annotation policies. To balance the different camera
exposures, approximately for half of the scenes the night cycle was annotated.
The custom annotation tool is also publicly available on GitHub.
|                  | # of scenes | # of images | # vehicle positions | # instances |
|-----------------|-------------|-------------|---------------------|-------------|
| **train**       |             |             |                     |             |
| day             | 113         | 19078       | 15403               | 45765       |
| night           | 145         | 25264       | 26615               | 72304       |
| **validation**  |             |             |                     |             |
| day             | 20          | 3898        | 2602                | 7244        |
| night           | 25          | 4322        | 3600                | 12746       |
| **test**        |             |             |                     |             |
| day             | 19          | 3132        | 3045                | 9338        |
| night           | 24          | 4052        | 3384                | 10438       |
| **total**       |             |             |                     |             |
| day             | 152         | 26108       | 21050               | 62347       |
| night           | 194         | 33638       | 33599               | 95488       |
| **cumulated**   | 346         | 59746       | 54649               | 157835      |

Table 1: Dataset split.

3.6 Statistics

The dataset contains 59,746 annotated images, spread over 346 scenes. In comparison to the Enz-dataset (Oldenziel, Ohnemus, and Saralajew, 2020), the share of indirect instances to direct instances is better balanced (ca. 43% of instances are indirect). The same is true when considering the detections of indirect vehicles (51% of the annotated vehicle positions are indirect). The total numbers of images, scenes and instances are summarized in Table 1.

4 Conclusion

In this paper, we have introduced the PVDN dataset that is conducted to evaluate and train algorithms to providently detect vehicles at night. Based on this annotated dataset—in accordance with the publication—we hope to provide a baseline to study “object” detection frameworks that are closer to human capabilities at night. Additionally, as discussed before, the proposed task gives good reasons why keypoint prediction frameworks are better suited in this case. However, the current trend in machine learning focuses more on bounding box predictions that might be cumbersome for light-artifacts. Finally, as most object detection benchmarks datasets focus on daylight scenarios, this dataset is

[https://github.com/larsOhne/pvdn](https://github.com/larsOhne/pvdn)
a good starting point to leverage object detection frameworks at night to the next level—as it is long overdue.

References

Alcantarilla, Pablo Fernández et al. (2011). “Automatic LightBeam controller for driver assistance”. In: Machine Vision and Applications 22, pp. 819–835. doi: 10.1007/s00138-011-0327-y

Eum, Sungmin and Ho Gi Jung (2013). “Enhancing light blob detection for intelligent headlight control using lane detection”. In: IEEE Transactions on Intelligent Transportation Systems 14.2, pp. 1003–1011. doi: 10.1109/TITS.2012.2233736

He, Kaiming et al. (2016). “Deep residual learning for image recognition”. In: Proceedings of the IEEE conference on Computer Vision and Pattern Recognition (CVPR), pp. 770–778. doi: 10.1109/CVPR.2016.90

Jurić, Darko and Sven Lončarić (2014). “A method for on-road night-time vehicle headlight detection and tracking”. In: 2014 International Conference on Connected Vehicles and Expo (ICCVE). IEEE, pp. 655–660. doi: 10.1109/ICCVE.2014.7297630

López, Antonio et al. (2008). “Nighttime vehicle detection for intelligent headlight control”. In: Advanced Concepts for Intelligent Vision Systems. Ed. by Jacques Blanc-Talon et al. Vol. 5259. Lecture Notes in Computer Science. Springer, pp. 113–124. doi: 10.1007/978-3-540-88458-3_11

Oldenziel, Emilio, Lars Ohnemus, and Sascha Saralajew (2020). “Provident detection of vehicles at night”. In: 31st IEEE Intelligent Vehicles Symposium (IV 2020), pp. 472–479. doi: 10.1109/IV47402.2020.9304752

Redmon, Joseph et al. (2016). “You only look once: Unified, real-time object detection”. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 779–788. doi: 10.1109/CVPR.2016.91

Ren, Shaoqing et al. (2015). “Faster R-CNN: Towards real-time object detection with region proposal networks”. In: Advances in Neural Information Processing Systems, pp. 91–99. URL: http://papers.nips.cc/paper/5638-faster-r-cnn-towards-real-time-object-detection-with-region-proposal-networks

Sevekar, Pushkar and S. B. Dhome (2016). “Nighttime vehicle detection for intelligent headlight control: A review”. In: Proceedings of the 2016 2nd International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), pp. 188–190. doi: 10.1109/ICATCCT.2016.7911989