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Let The Sunshine in: Sun Glare Detection on Automotive Surround-view Cameras

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ABSTRACT

Sun glare is a commonly encountered problem in both manual and automated driving. Sun glare causes over-exposure in the image and significantly impacts visual perception algorithms. For higher levels of automated driving, it is essential for the system to understand that there is sun glare which can cause system degradation. There is very limited literature on detecting sun glare for automated driving. It is primarily based on finding saturated brightness areas and extracting regions via image processing heuristics. From the perspective of a safety system, it is necessary to have a highly robust algorithm. Thus we designed two complementary algorithms using classical image processing techniques and CNN which can learn global context. We also discuss how sun glare detection algorithm will efficiently fit into a typical automated driving system. As there is no public dataset, we created our own and will release it publicly via the WoodScape project [1] to encourage further research in this area.

I INTRODUCTION

There are many sensors that are used in the development of autonomous driving vehicles, the more common being cameras, lidars, radars and ultrasounds. Cameras are one of the vital sensors as it is possible to get semantic, structural and navigational information from the images they provide [2, 3]. Besides almost all vision based algorithms depend on the image data coming from this sensor. Recently, there is rapid progress in various visual perception tasks such as semantic segmentation [4, 5, 6], moving object detection [7, 8], depth estimation [9, 10], re-localisation [11, 12], soiling detection [13, 14], etc.

Sun glare, either direct or reflected, is a known issue while driving as the driver can be temporarily blinded by the light. This is especially the case when the sun is low in the sky (winter) and the sunshades cannot protect the driver's eyes. The sudden event of temporary blindness is quite precarious to keep driving safe. A recent study [15] shows that during bright sunlight, the chance of car crash is about 16% higher than normal weather. The same issue due to the glare effect is well observed in automotive cameras. Paradoxically, we can say that bright sunlight is yet another case of the adverse weather scenario which complements the well known set of scenarios [16].

The sun glare effect can be categorized into two classes—direct and indirect. When the sun is low in the sky then the glare directly hits the eyes. This scenario represents direct sun glare.

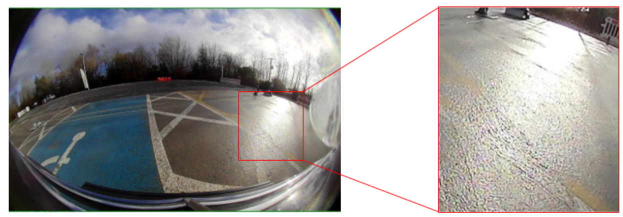


Figure 1: Illustration of sun glare causing perception issues. The zoomed in region shows wiping off lines.

On the other hand, the sunlight reflected from the wet road or highly specular surface causes indirect sun glare effect. Another issue with indirect sun glare is that the detection of lane markings becomes almost impossible as the region with the glare effect is overexposed, washing out the lane markings boundaries. In Figure 1, we depict a nice example of indirect sun glare effect on lane markings. We can expect certain degradation of accuracy in detection of this particular lane marking. In some cases, the misdetection of road markings may negatively impact the decision on driving direction of the autonomous system. As the community aima to achieve the Level-5 Autonomous Driving system [17] that has to work under any circumstances, it is important that cameras are able to detect if there is any decline in the image sensor processing reliability ([18, 13, 19, 16, 14]) and are also more robust to these common lighting conditions. Ignoring this problem could lead to unprecedented events.

The main contributions of this paper are as follows:

1. Introduction and formal definition of a sun glare detection task in automotive scenarios for surround-view cameras.
2. Release of the first public sun glare dataset as a part of WoodScape dataset project [1].
3. Implementation of a baseline sun glare detection algorithm and experimental evaluation.

The paper is organized as follows. Section II discusses related work on sun glare detection in the automotive industry. Section III describes the design of a sun glare dataset. Section IV presents the algorithms, experimental evaluation, and results analysis. Finally, Section V summarizes and concludes the paper.

II SUN GLARE DETECTION TASK

This section comprises of a brief overview of related work on the sun glare detection in the automotive industry . A sun glare has always been an issue for manual driving and is becoming a real

Figure 2: Screenshots from the video [20] showing that sun glare can wash out important information from the images (Left: 2'57, Middle: 3'00, Right: 3'02

problem for autonomous driving as well. This is because it is blocking critical information to be collected by the camera from the overexposed region. This section discusses the related work done in this area.

Scott Kubo, a YouTuber, is regularly sharing videos about the autonomous driving system. In his video [20] from March 2019, he shows the behavior of the autonomous driving mode when driving directly towards the sun. In the video, it can be observed that the sunlight is reflecting on a part of the road and is washing off the lines on the ground. At the beginning of the video ($1'05$), Scott is asking the car to change the lane while the glare is huge on the ground, the car starts to change the lane but then goes back to its original one. It can be presumed here, more than likely, the absence of the information on the right lane (due to the sun glare) blocks the car to take the decision of changing the lane. Later in the aforementioned video, it can be observed that the sun in the sky is so strong that it wipes out the bridges and cars that are just in front of the host car. The Figure 2 depicts three screenshots from that video and demonstrates the impact of sun glare on the images in different scenarios. This video manifests the importance of being able to detect the sun glare as its misdetection can be very dangerous.

Regarding human driving, Bosch presented a Virtual Visor at the CES 2020 [21]. Their concept uses a transparent LCD panel with a camera facing the driver [22]. Using artificial intelligence, the camera is able to detect and recognize part of the face of the driver. When sun glare is detected and is blinding the the driver, then part of the LCD panel shades the driver's eyes. Virtual Visor was named Best of Innovation in CES 2020 Innovation Awards. The Figure 3 is an image extracted from the press release from Bosch and shows the concept of the Virtual Visor.

In the paper [23], the authors proposed a method to generate spatio-temporal distribution of the occurrence of sun glare using publicly available panorama images from Google Street View. Later, convolutional neural network (CNN) used to segment these images and predict the glare created by the sun.

Andalibi et al. [24] presented an algorithm for automatic real-time glare detection using a combination of photometric, geometric and GPS information to compute the solar azimuth and elevation.

In [25], the author presented a solution to accurately detect sun glare on the road at any time by calculating the sun's position and taking the surrounding terrain into account including prediction of sunrise and sunset time. The solution also provides a plugin for visualizing the results.

For the cameras, as the high intensity light hits the image sensor, pixels are saturated and large areas of over exposure can appear on the image completely washing out the detail in the area. In Figure 1, the yellow road markings are wiped out from the image because of the sun glare. The sun glare artifact is usually

Figure 3: Image extracted from Bosch press release [22] demonstrates Virtual Visor

produced by the reflection on wet road/cars, highly specular surfaces/materials or by direct light. The Figure 4 shows examples of sun glare on automotive cameras. It is clear, that sun glare can be an issue for computer vision algorithms attempting to detect detail in these image regions. As we push towards autonomous driving, it is key that cameras are more robust to these common lighting conditions and are able to detect when there is a degradation of functionality to warn the system or user of reduced or unreliable performance.

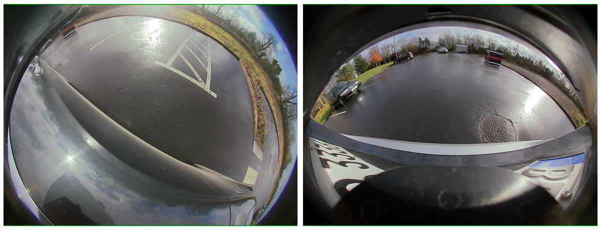
III DATASET DESIGN

This section explains how the sun glare dataset has been created. Section III. A provides the requirements of the dataset. Section III. B explains the methods used to do annotation. Finally, Section III. C describes the WoodScape [1] dataset, in which the sun glare dataset will be made available to the public in the next few months.

III. A Dataset Design

A dataset that contains images with sun glare effects has been created as to the best of our knowledge there are no public datasets available to address the presented problem. Fisheye cameras are widely used in the automotive industry because they offer a wide field of view (FoV). Four cameras are installed on a moving vehicle capturing the full surround view of the vehicle (one front view, two side-mirror views and one rear view). The dataset is composed by images recorded in two different countries. The typical scenarios we are interested in are when the sun glare is present on an image (in the sky and/or on the road) from one of the cameras. The following list gathers different scenarios of sun glare and details the dataset content:

- Sun glare due to the reflection of the Sun on the ground plane (whatever the surface: road, water, snow, etc.).
- Sun glare regions that are due to the reflection of the Sun on vertical objects with specular surface/material (e.g.: cars, trucks, signs, etc.).
- Sun glare due to direct Sun.
- Sun glare regions on the car body of the ego vehicle due to the Sun.
- Images without Sun glare.



(a) Sun glare on wet road wiping off road mark

(b) Left: Sun glare on wet road and in the sky. Right: Sun glare on dry road and in the sky

(c) Left: Sun glare in the sky reflecting on water. Right: Sun glare in the sky amplified by soiling on the lens

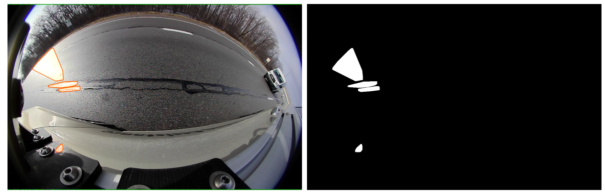
Figure 4: Diverse Scenarios captured in our WoodScape Sun glare Dataset

III. B Dataset Details

It is very difficult to annotate a sun glare as there are no definite boundaries around them. A sun glare, as defined in the earlier section, is a part of the image, where the pixels are over-exposed. This is why it has been chosen to annotate the dataset using automatic annotation followed by a manual check. Some image processing techniques, for example thresholding and morphological operations are used to detect regions where the sun glare effect is found more than likely. Unfortunately, the polygons created using this technique do not differentiate the sun glare effect with other very bright/white objects in the image. This is why a manual check was added in the annotation process. Each image has been visually checked by an annotator and decision such as discarded/validated was made. The created dataset has been split into two parts [26]: a training set which contains around $1,115$ images (580 images with sun glare and 535 images without sun glare), and a test set of around 294 images (184 images with sun glare and 110 without sun glare regions). Uncertainty maps with probability per pixel for each images are provided as well. The Figure 5 is showing example of the annotation.

III. C WoodScape

WoodScape is a comprehensive multi-task multi-camera fisheye dataset for automated driving. Figure 6 illustrates various tasks planned to be part of the release. It comprises of classical vision tasks such as object detection and semantic segmentation,



(a) Left: Image annotated with sun glare regions. Right: Corresponding mask annotation

(b) Left: Image annotated with sun glare regions. Right: Corresponding mask annotation

Figure 5: Examples of images annotated

and geometric tasks like depth estimation and motion estimation. We would like to augment this dataset to include sun glare task as well. Sun glare dataset images are completely separate from other datasets. This is the reason we explore it as a separate task rather than augmenting it with segmentation where sun glare region is an additional class. This way the dataset design for sun glare can be flexible and extensive without coupling with other tasks. Annotation formats and folder structures for sun glare task will be consistent with other tasks.

IV PROPOSED ALGORITHM AND RESULTS

In this section, we describe the system perspective context (Section IV. A), then the two proposed algorithms, specifically the image processing baseline (Section IV. B) and the CNN baseline (Section IV. C).

IV. A System Perspective

Deploying a single network dedicated only for one task is always expensive on any embedded platform. Recent trends of Multi Task Learning (MTL) for vision based tasks can be leveraged in this case. As the sun glare detection task is quite different than other perception tasks such as semantic segmentation, object detection etc., so we plan to use a pre-trained shared encoder and task specific decoders to train the sun glare detection task as a separate decoder as shown in Figure 9.

As a step towards making sun glare detection more robust, the output from classical algorithm and predictions from CNN can be fused using uncertainty map. This will lead us to achieve sun glare tracking. By merging the sun glare detection as a part of other vision based tasks through MTL, we can reduce the computation complexity at least by half [27]. This way the pre-trained shared encoder can be used as an efficient feature extractor that has good understanding of the automotive scenes during the training of other tasks. Our baseline of semantic segmentation and object detection network details are described in [28, 29]. Besides, end-to-end joint training of all tasks can be done to see the impact

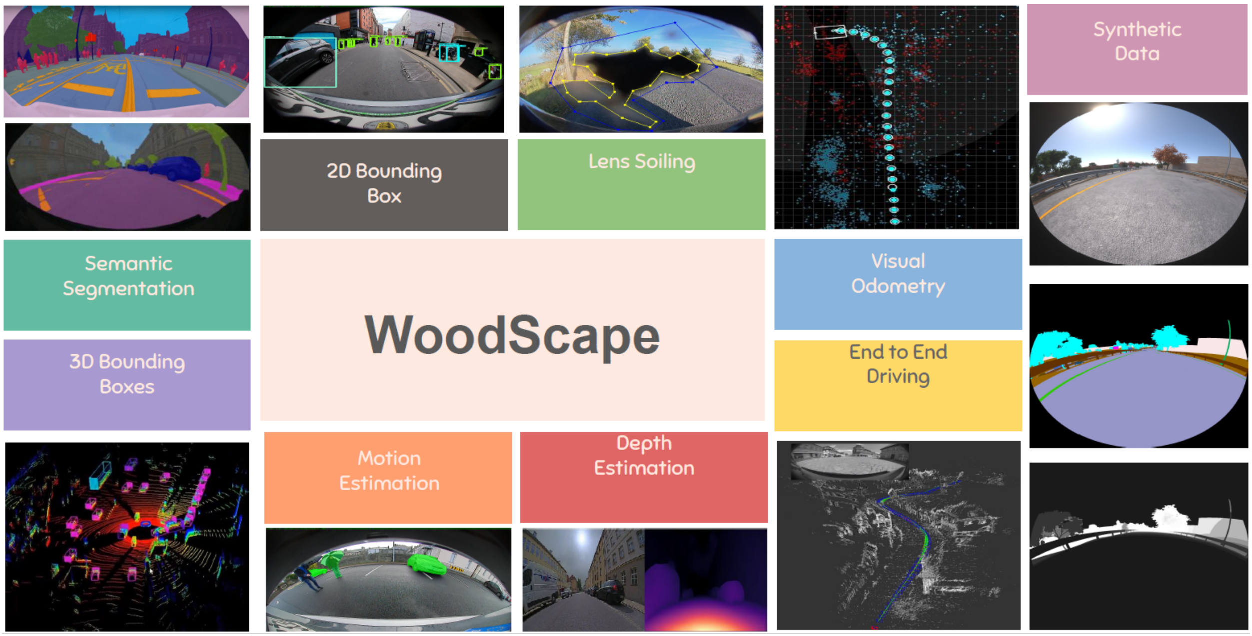


Figure 6: Illustration of the main tasks in our WoodScape dataset [1]

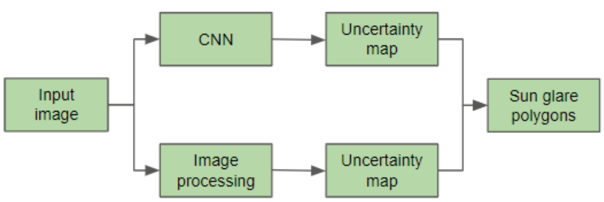


Figure 7: Fusion of image processing and CNN results using uncertainty map

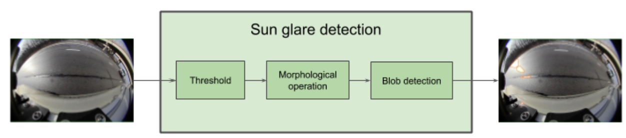


Figure 8: Image processing algorithm scheme

on KPI of other decoder outputs due to the addition of the sun glare detection.

Based on the problem explained in the previous section, we are proposing a new method for sun glare detection (direct or indirect sun glare) by combining information given by image processing filters and multi-camera tracking. This can be used to either enhance processing in this region, change tracking criteria to limit the system functionality, or to simply inform the system about a threat of a potential performance degradation. An example of this would be camera based lane sensing on a straight wet road with the vehicle travelling towards the sun which is low in the sky. In this case, detection accuracy and range would be severely impacted and hinder the lane assist functionality severely.

IV. B First Solution: Image Processing Algorithm

An image processing algorithm is used to detect sun glare using different processing blocks, such as color conversion, adaptive thresholding, geometric filters and blob detection. By getting information from image processing, we can find a redundancy between regions detected as saturated using image processing and CNN output. This image processing algorithm is different than the annotation algorithms as thresholds and morphological operations applied are different. To avoid having the same issue as the one encountered in the automatic annotation algorithm, such as white objects detected as sun glare, thresholds, morphological operations and blob detection blocks are used using sharper values.

First, the image is converted into the YUV color space before applying a threshold in order to get only pixels that are potentially over-exposed (pixel value of 255). To remove noise, a closing operation has been applied followed by an erosion operation which removes small objects so that only substantive objects remain. The blob detection step starts by finding the contours using the method that stores all the contour points and the mode to retrieve only the outer contours. Finally, polygons are created using the convex hull method. The size of the polygon is checked as we do not want to detect sun glare regions that are smaller than a specified threshold. This size differentiation removes some of the false detections. The Figure 8 shows the steps of this image processing algorithm.

The algorithm has been tested on 300 images from the test set and KPIs (Key Performance Indicators) have been determined as follows:

- True Positive (TP): proportion of pixels detected and annotated as “sun glare”.
- False Positive (FP): proportion of pixels detected as “sun glare” but annotated as “no sun glare”.
- False Negative (FN): proportion of pixels detected as “no sun glare” but annotated as “sun glare”.
- True Negative (TN): proportion of pixels annotated and detected as ”no sun glare”

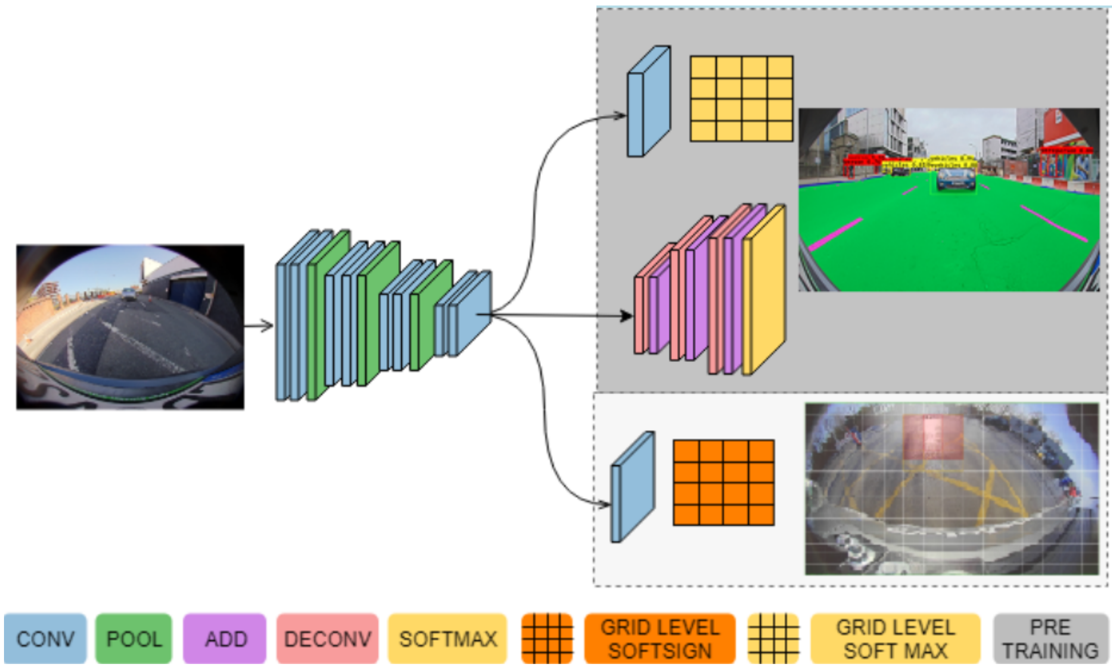


Figure 9: Illustration of how sun glare detection CNN model will be part of a pre-trained Multi-Task Learning model

From the the KPIs detailed in the previous list, precision ($Precision = \frac{TP}{TP+FP}$) and recall $Recall = \frac{TP}{TP+FN}$ metrics have been calculated.

- $Precision = 85\%$
- $Recall = 96\%$

Table 1: True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN)

Average TP	96.23%	Average FP	16.41%
Median TP	97.49%	Median FP	18.2%
Average FN	3.8%	Average TN	99.4%
Median FN	2.5%	Median TN	99.5%

IV. C Second solution: CNN

We make use of the WoodScape sun glare dataset ground truth for training a fully convolutional neural network. In Figure 10, we depict the CNN's architecture, the building blocks are denoted as follows: convolution blocks (blue in the Figure 10) encode the kernel size, stride, number of output channels, following type normalization (if any) and an activation layer. So, "c7s1-32-IN-R" reads as a 2D convolution layer with kernel size 7 pixels, stride 1 pixel, 32 output channels, followed by instance normalization layer and ReLU activation layer. "S" in the last convolution block stands for the Sigmoid activation layer; residual block (purple in Figure 10) consists of a 2D reflection padding layer, followed by a 2D convolution layer with kernel size 3, the same number of input channels as the output channels (64), followed by the batch normalization layer and ReLU activation; finally, upscaling block (yellow in Figure 10) is a nearest-neighbor upsampling layer by a factor of 2.

We train our network via Adam optimizer [30] with learning rate set to 1×10^{-4}, $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\varepsilon = 1\times10^{-8}$, we let the network train for 200 epochs. As the loss function evaluating the necessary gradient changes, we use the cross entropy loss. To better utilize the small number of training samples, we use the simple data augmentation consisting of random cropping with 12% in both width and height, random horizontal and vertical flipping, and random rotation by 180°. The probability of all augmentations is set to 0.5, except of the random cropping, which happens always. Since the annotations are not 100% precise and due to lack of data, we let the network to be trained for full 200 epochs, without formulation of any reasonable stopping criterion.

For evaluation on the test set, we opted for the commonly used mean Intersection over Union (mIoU), also known as the Jaccard score. However, we noticed there are several problems in our specific task which concerns usage of imprecise ground truth labels. Theoretically, there are 4 distinct cases that might occur in sun glare semantic segmentation IoU evaluation. However, one is highly unlikely as it covers the case when whole image would belong to the sun glare class. Therefore, we will limit ourselves to only three common cases. The first case is when both classes are represented in both ground truth label and the prediction. The second case is formed by an image which is not affected by sun glare and correctly recognized as such (i.e. both ground truth and prediction are represented only by "clean" label). The last, third, case is described by a situation when sun glare is detected in a "clean" image.

The problem is that in the last case, the mIoU does not reflect how bad the prediction was. In our experiments, we frequently spot incorrect classification of sun glare in just a few pixels, however in terms of the mIoU, this leads to radical drop towards 0.5. Another problem is the imprecise annotation, which affects the first case as well— since the labels are imprecise, mIoU going to 1.0 is actually not good.

We would like to emphasize that we are aware of the limits of

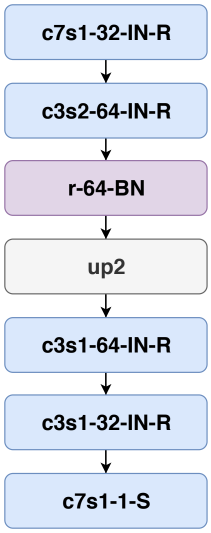


Figure 10: Proposed sun glare CNN architecture. Description of individual components is in the text.

Table 2: Results from the CNN experiment. Each case is detailed in the text. Class 0: Background — Class 1: Sun glare

CASE 1	IOU	mean	std	median	min	max
Class 0	99.01	98.46	1.04	98.94	94.91	99.73
Class 1	51.28	51.49	13.68	51.19	8.06	77.76
CASE 2	IOU	mean	std	median	min	max
Class 0	100	100	0	100	100	100
Class 1	100	100	0	100	100	100
CASE 3	IOU	mean	std	median	min	max
Class 0	0	0	0	0	0	0
Class 1	0	0	0	0	0	0

the proposed approach and consider it as a baseline solution. We want to investigate the possibilities of a weak supervision, providing a more principled way of dealing with the aforementioned issues.

IV. D Discussion

The goal of this work is to emphasize the importance of the sun glare detection which is relatively less explored in automated driving. To enable further research, we created a dataset comprising of diverse and challenging scenarios. We implemented two basic prototypes using traditional image processing and deep learning. The false positive rate of 16% in the image processing approach demonstrates that the problem is not easily solvable using a simple classical approach. To our surprise, the semantic segmentation model achieves only a moderate IoU of 51 for sun glare regions. We outlined the problems with the mIoU metric, which explain this "low performance". However, it also demonstrates that the sun glare detection is a challenging problem and needs a larger design effort. We see it also as an opportunity for further investigation by the community.

V Conclusion

Sun glare detection is an important problem for higher levels of automated driving. But this topic is not explored in detail in the

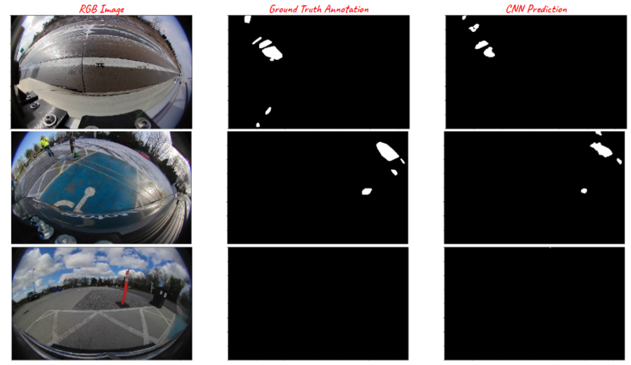


Figure 11: The visual comparison of several testing examples. Left to right: original RGB image, ground truth annotation, CNN prediction.

community as there is no public dataset available. Thus we created a new dataset and will release it as a part of the WoodScape project [1]. We developed two prototypes using CNN and classical image processing approach and we intend it to be baselines for the dataset. In future work, we plan to perform a fusion of both approaches and also integrate the CNN model into a multi-task network.

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Michal Uřičář *received MSc. degree (major in computer graphics and minor in computer vision) from Czech Technical University in Prague in 2011, and Ph.D. from the same university (in 2018) while working in the machine learning group of the Center for Machine Perception under the supervision of Dr. Vojtěch Franc. His Ph.D. thesis got in the final round of Antonin's Svoboda and Werner von Siemens awards for best Ph.D. thesis of the year. Since 2016, he is working as a researcher in Valeo R&D, Prague. His main research focus is machine learning, with applications in computer vision. He received the best paper prize at VISAPP in 2012 and the 3rd place at Looking at People Challenge: Age estimation track, organized at CVPR 2016. In 2019, Michal was awarded the Expert status in Valeo for Machine Learning. He is in TC for several conferences and journals (e.g. ICPR, PRL, TIP, NCAA).*

Arindam Das *is a senior engineer in the department of Detection Vision Systems (DVS) at Valeo India. He is currently involved in deep learning based algorithm development activities in autonomous driving systems. He has over 6 years of industry experience in computer vision, deep learning, raster image processing and document analysis. He has authored 11 peer reviewed publications and 21 patents including 15 grants. He is a member of the Irish Pattern Recognition and Classification Society (IPRCS), a member body of the International Association for Pattern Recognition (IAPR).*

Senthil Yogamani *is a computer vision architect and technical leader at Valeo Vision systems. He is currently focused on research and design of the overall computer vision algorithm architecture for surround-view camera visual perception in au-*

tonomous driving systems. He has over 14 years of experience in computer vision and machine learning including 11 years of experience in industrial automotive systems. He is an author of 80 publications and 50 patents. He serves in the editorial board of various leading IEEE automotive conferences including ITSC and ICVES and advisory board of various industry consortia including Khronos, Cognitive Vehicles and IS Auto. He is a recipient of best associate editor award at ITSC 2015 and best paper award at ITST 2012.

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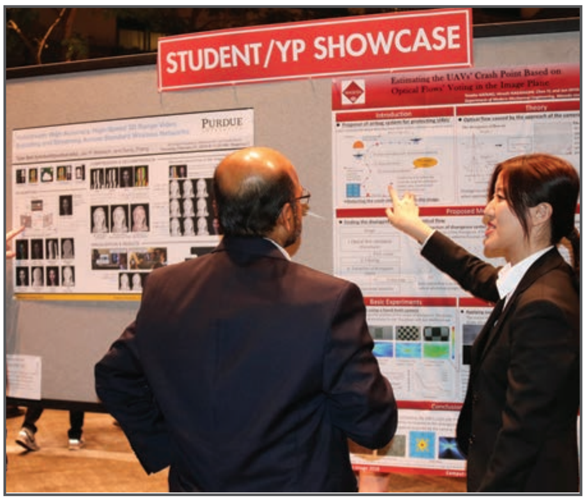

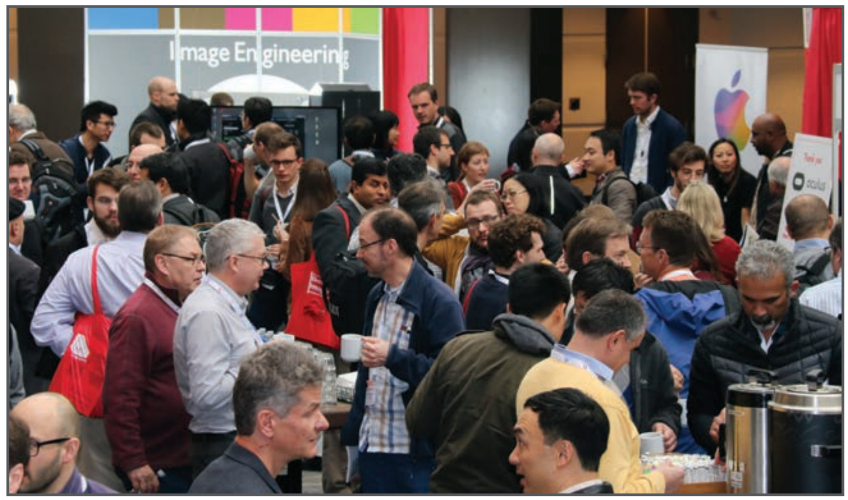

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