Energy-Efficient Illumination by Matrix Headlamps for Nighttime Automated Object Detection

Mirko Waldner[1,*], Nathalie Müller[2] and Torsten Bertram[3]
[1]Institute of Control Theory and Systems Engineering (RST), TU Dortmund University, Dortmund, Germany
Email: mirko.waldner@tu-dortmund.de
[2]Institute of Control Theory and Systems Engineering (RST), TU Dortmund University, Dortmund, Germany
Email: nathalie2.mueller@tu-dortmund.de
[3] Institute of Control Theory and Systems Engineering (RST), TU Dortmund University, Dortmund, Germany
Email: torsten.bertram@tu-dortmund.de
[*] *Corresponding author*

Abstract: **The contribution at hand presents a novel approach to generate dynamic energy-optimized illumination by matrix headlamps designed for automated driving. The approach consists of a novel basic minimal illumination adapted to the current road environment with minimum brightness and a light pixel control strategy to adjust the illumination of potential objects uniformly and selectively only. The approach was developed and optimized by considering the impact of other lighting functions such as Glare-Free High Beam and marker light on the quality of object detection and possible alternatives such as symbol projection with structured light. The concept achieves a similar quality of object detection as conventional high beam, but requires only around 16% of the energy. This shows the energy saving potential of automated vehicles in combination with novel headlight control strategies.**

Keywords: **matrix headlight, automated driving, energy optimization, lighting functions**

I. INTRODUCTION

Reducing the total electrical energy consumption and CO_2 production of automotive matrix headlights and the optimization of their dynamic lighting functions [1] are important aspects of product development to increase the range of electric vehicles and create sustainable products with positive reputation [2]. One simple and economical way to lower headlamp energy consumption during operation is to reduce the emitted luminous flux of all individual headlamp light sources, but this also decreases the contrast and visibility of dangerous traffic objects. High-Definition (HD) matrix headlights, which are often called pixel or digital headlights, consist of many individual light modules, each of which can have up to 1.3 million individually controllable light sources called pixels [3], which are arranged in a matrix format and illuminate different areas in front of the ego vehicle. By using a matrix headlight, the illumination in front of the ego vehicle is therefore area-selectively adjustable in brightness, enabling lighting functions such as Glare-Free High Beam (GFHB) [4,5] and the projection of symbols like a crosswalk for visual communication. The GFHB lighting function allows the high beam to be kept active while other road users are in front of the ego vehicle without dazzling them by selectively turning off those pixels whose illumination would dazzle other road users and keeping the rest of the high beam illumination active. The GFHB is shown in fig. 1 as the dark tunnel in the simulated fog around the vehicle in the distance. The red ego

Fig. 1: Simulation of HD lighting functions such as GFHB, projecting the planned path of the automated vehicle onto the road and marking dangerous traffic objects with projected lines to direct the human driver's attention [6].

vehicle in fig.1 is equipped with a pair of HD matrix headlights which each have over 100k individual light sources, so it is possible to project symbols [6] on the road additionally to the ordinary GFHB. Here, the pedestrian is marked with a projected line to warn the human driver and guide its attention and a possible evasive maneuver to avoid a collision with the vehicle without lights on the driving lane is projected as a polygon curve.

Currently used high beam illumination is generally optimized for the best environment perception of the human driver and not for automated vehicles, especially their cameras and information processing with machine learning. Since high beam illumination is intended to improve visibility of traffic objects, it should also be suitable for object detection with cameras, but the question is whether currently used GFHB is the most energy-efficient illumination for an automated vehicle or whether there are better options with the same quality of object detection. Unlike a human driver, an automated vehicle is able to quickly communicate its confidence about a potential traffic object to the headlight

This work is funded by the German Federal Ministry for Economic Affairs and Climate Action as part of the AHEAD-project (grant number: 19A21021C). The responsibility for the content of this contribution lies with the authors.

control system, which could selectively and rapidly adjust the HD illumination to improve detection. This control loop is not possible with a human driver because there is currently no human-machine interface for pixel control in vehicles. As automated driving continues to evolve, it is conceivable to develop such a control loop between matrix headlights and the environment perception algorithms that offers the potential to illuminate the environment more efficiently, primarily by using less electrical energy for the same quality and by being more targeted to objects of interest.

Considering a possible novel control loop, this contribution presents a novel approach for optimal illumination, which consists of a novel Adaptive Frontlighting System (AFS) basic static illumination and a corresponding control strategy for maximizing the quality of visual camera-based object detection by deep learning in an energy-efficient manner. In contrast to the state-of-the-art and other work, the illuminations in this paper are designed to provide optimal support for highly automated driving, not for human drivers and other human road users. The presented strategy uses a minimum brightness baseline illumination, which is only bright enough to detect anything at all, and an adaptation strategy of pixels emitting in the direction of the detected object to improve its detection. Therefore, the novel illumination may be perceived as too dark for humans, but the automated vehicle can still just barely detect all objects. Object detection involves finding the correct position, rotation, and size of the bounding box around the object and the class of the object. Detection of objects such as vehicles at night with machine learning is not a new research topic [7], [8] and the contribution at hand focuses on energy efficient enhancement of environment perception with existing state-of-the-art machine learning approaches such as YOLOv5 [9]. Optimal illumination using matrix headlights for object detection is also evaluated by [10], which evaluates the minimum illumination required to localize objects with a Intersection over Union (IoU) [11], also called Jaccard index, of 50% on validation data. This previous work uses single static light distributions and does not consider dynamic features such as GFHB and marker light. Also, this previous work seams to adjust the complete light distribution in front of the ego vehicle and is not using the novel approach of this contribution of using a minimal base illumination and adjusting only the illumination in the area of the objects. Adjusting the complete beam pattern has as the disadvantage a higher energy consumption and an increased subjective level of distraction of road users due to a larger area of changing lighting. In contrast to the published work, this contribution not only discusses the minimum illumination required for reliable object detection, but also presents and compares strategies to use HD matrix headlights to improve detection quality, e.g., the IoU of detected objects, while considering dynamic illumination features that may interfere with object detection.

For object detection, section II briefly discusses the creation of a minimum base illumination, which should be generated dynamically considering the current environment. Then, it is assumed that all objects are detected in any way. In section III strategies to efficiently improve detection of vehicles and pedestrians under uniform illumination by the matrix headlamps are presented and in section IV the projection of symbols such as structured light with line patterns and randomized patterns are evaluated and compared to improve object detection. The summary and outlook in section V concludes the contribution at hand.

II. CREATING THE MINIMAL BASE ILLUMINATION

An optimal illumination should maximize visibility and assessability of the traffic situation with minimal energy expenditure and without disturbing any road user including animals and artificial intelligences. Since further AFS basic illuminations for automated vehicles are not yet standardized, this section is highly subjective and represents the opinion of the authors. According to [12] and in the authors opinion' further HD illumination should be dynamically adjusted to environmental segments such as the roadway, shoulder, bike lanes, and buildings to optimally illuminate the various environmental objects, e.g., increased illumination around parking cars to better detect children running onto the road. Therefore, it is proposed to use minimal illumination as a baseline and selectively increase and adjust the illumination based on the environment class, e.g., additional light on the bike lane or reduced light on highly reflective buildings to generally provide optimal illumination.

A test scenario is used to develop and evaluate the baseline illumination and illumination control strategy. The test scenario is similar to [10] and has a two-lane, straight road with a lane width of 3.5 m, which is shown in fig. 2 from an orthographic perspective from top to bottom. This scenario has 16 test positions $\boldsymbol{p}_{x,y} = [x\ y\ 0]^{\mathrm{T}}$ with longitudinal position x and lateral position y. The origin of the right-handed coordinate system is between the headlights of the ego vehicle. The test positions $\boldsymbol{p}_{x,y}$ are located at longitudinal distances of 25 m, 50 m, 75 m, and 100 m, as well as laterally in the middle of the lanes and directly at the edges of the lanes. The positions $\boldsymbol{p}_{x,y}$ were chosen to represent subjectively interesting test cases because objects at 25 m could require immediate driver intervention, objects at 50 m are at the edge of the range of an average low beam, objects at 75 m should not be visible with a typical low beam, and objects at 100 m are at the edge of the range of an average high beam. The range of a headlight depends on the lighting technology used, so the values given are subjective and depend on personal experience.

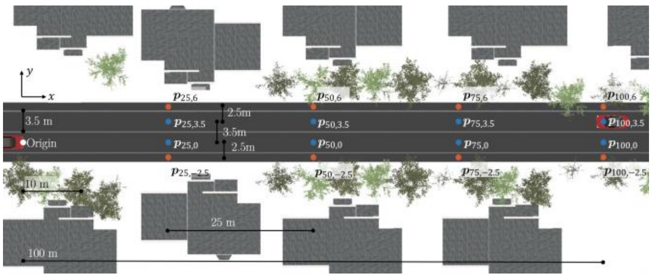


Fig. 2: Orthographic top-down visualization of the test scenario setup of a straight two-lane country road and additional environment objects with 16 test positions $\boldsymbol{p}_{x,y}$ similar to [10].

The test objects are a vehicle with red metallic paint and a length of 5.1 m, a width of 2 m and a height of 1.6 m and a dark light blue stylized male person with a height of 1.8 m and a width of 0.8 m. During the research for this contribution, the size, material, and color of the objects were slightly changed, resulting in similar but not identical results. The exact influence of the object parameters will be investigated in a further contribution.

For real time lighting simulation, the Unreal Engine (UE) 4 was chosen and trees, marker posts and houses are placed near the road to create a realistic virtual country road scene. No scheme was followed in the manual placement of objects, nor was a real street recreated. The Physically Based Rendering (PBR) material-parameters were chosen empirically to create a realistic-looking environment with the Twinmotion material collection as a starting point.

Fig. 3a shows conventional high beam illumination and in contrast fig. 3b shows a novel optimized illumination for automated vehicles with minimum brightness. In the far field, the illumination is empirically reduced to the minimum light intensity required for detecting vehicles at all positions $\boldsymbol{p}_{x,0}$ and $\boldsymbol{p}_{x,3.5}$ for increasing distance in x-direction with $x = 25$, 50, 75, 100 (as shown in fig. 2) and people at position $\boldsymbol{p}_{x,-2.5}$ and position $\boldsymbol{p}_{x,3.5}$. The automated vehicle is assumed to travel in its straight lane, so it is not necessary to detect for example objects at position $\boldsymbol{p}_{x,6}$ and it is sufficient to detect them when they are at position $\boldsymbol{p}_{x,3.5}$ to avoid dangerous situations. If the further path of the ego vehicle is changed, the base illumination must be adjusted to ensure the detection of safety-critical objects.

(a) High beam at 100 % usage, which would dazzle other traffic participants.

(b) High beam at 8 % usage and deactivated illuminations at both sides.

Fig. 3: Comparison of the default high beam and novel optimized beam pattern in a simulated scene. The class, confidence and bounding boxes of the YOLOv5 [9] object detection are also shown.

The energy-optimized illumination in fig. 3b consists of a basic illumination directly in front of the ego vehicle, which mainly ensures that the vehicle is seen by others rather than enhancing its own perception, and a high beam reduced to 8% of its default usage. In addition, all pixels that illuminate areas above a threshold height value outside the lane are disabled by default to save energy. The illumination height increases with distance, so that a person 100 m away is fully illuminated and only the legs of a person 50 m away are illuminated and thus visible. To detect distant persons, a larger area of the body must be illuminated, because the person covers a smaller number of pixels in the camera image. With this illumination, people can be detected at all positions $\boldsymbol{p}_{x,-2.5}$ and $\boldsymbol{p}_{x,3.5}$ with YOLOv5 [9], ensuring object detection. Dimming of high areas next to the road could prevent automatic detection of traffic signs, but if the vehicle's environment perception is able to detect the sign's pole or use map information about upcoming signs, then the headlight control algorithm could dynamically increase illumination in the expected area of the sign to ensure its readability. However, since traffic signs reflect light, they become unreadable if they are too brightly lit and dazzle the driver himself, so too much illumination is safety critical.

In order to improve the detection of objects and eliminate false detections caused by low illumination, the general strategy in this contribution is to increase the illumination of objects and their surroundings, but taking into account the behavior of traffic signs, there may be too strong illuminations that disturb the driver himself, e.g., by highly reflective surfaces. That is why, the next sections will show experiments to find efficient illumination levels, which improve the detection and not disturb the system with false classifications.

III. SELECTIVE 3D ILLUMINATION OF OBJECTS

For the development and evaluation of energy-efficient illumination, the scenario in fig. 2, is used. The scenario is simulated using Unreal Engine (UE) 4 with the default automatic histogram-based exposure calculation of the virtual camera with an exposure compensation of -1. The UE exposure calculation is designed to simulate human eye adaptation to changing environment brightness levels and is used to recreate an automatic camera parameter adaption. The virtual camera has an aperture angle of 60° and captures a 1920×1200 pixel image. The tests are only conducted in a virtual world, but [13] has shown that a properly adjusted Unreal Engine 4 provides similar and valid results in visually based studies with human subjects for headlight evaluation as a field test in reality. The illuminance, setup, and basic illumination, e.g., high beam matrix headlights of the ego vehicle, are modeled after real headlights manufactured by HELLA GmbH & Co. KGaA. Due to a Non-Disclosure Agreement (NDA) the setup cannot be explained in detail. In addition to the basic illumination directly in front of the vehicle, the matrix headlight in this paper has a modeled light module using the flexible modeling approach in [14]. The headlight module has a horizontal beam angle of $\pm 20°$, a vertical beam angle of $\pm 5°$, the aspect ratio is 4:1, similar to [15], and has 256 pixel rows and 1024 columns for a total amount of 262,144 pixels. The illumination area of all pixels overlaps with the area of their neighbors. The intensity of the headlights of the oncoming vehicles is empirically lowered to create a realistic appearance and reflections in the camera images.

For object detection, the "YOLOv5x6" model was chosen from the YOLOv5 network pre-trained on the COCO dataset [9], which contains mainly day images and has 80 object categories. The network is therefore not trained and optimized for traffic object detection at night with matrix headlamp illumination, so the results in this paper will not be the best possible, but this contribution is a kind of preliminary study as a starting point to identify promising approaches to be used in further work to select and train the right network. The authors expect the best and most efficient results from a combination of novel lighting functions for illumination and a specialized and trained network for detection.

The matrix headlight is simulated in real time [16] using Compressed Sparse Row (CSR) sparse matrix vector multiplication with CUDA [17,18] on a graphic card (GPU) and controlled using the Super Sampling Control (SSC) approach [6,19]. SSC computes the optimal utilization of all pixels starting from 3D target objects called primitives, e.g. cuboids or surfaces, so that the illumination of the headlamp best matches the desired illumination in shape and brightness. For example, GFHB is realized by a target cuboid primitive around the upper part of the oncoming vehicle that must not be illuminated by the matrix headlamp, which means that the target intensity in this 3D region is set to zero. Fig. 4 shows a more complex scene where lines are projected as structured light [20] as a kind of 3D scanning for potentially improved landmark detection from a pair of matrix headlights. Here, the primitives are planes consisting of the target lines as an image. The position and rotation of the lines is determined by the placement of the primitives in the world in front of the ego vehicle.

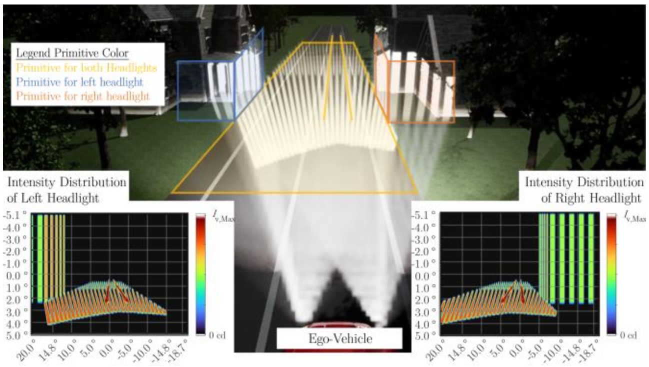


Fig. 4: Example of projecting symbols consisting of lines with matrix headlights controlled by SSC. The yellow primitives are considered by both headlights and the blue only by the left and the red only by the right one.

For an objectified and quantitative evaluation and rating of the quality of support of the object detection, this contribution proposes two evaluation criteria. One is the correctness and confidence of the classification and the other the Generalized Intersection over Union (GIoU) [11] of the detected rectangular bounding box to the true or reference bounding box. The confidence is the probability that the object belongs to the detected class and the GIoU is according to [11] the "similarity between two arbitrary shapes (volumes) $A, B \subseteq \mathbb{S} \in \mathbb{R}^n$". With the smallest enclosing convex object $C \subseteq \mathbb{S} \in \mathbb{R}^n$ of A and B the GIoU is

$$\frac{|A \cap B|}{|A \cup B|} - \frac{|C \setminus (A \cup B)|}{|C|}. \quad (1)$$

The first part of this formula is the IoU and the second part ensures that the formula becomes < 0 when A and B do not intersect [11]. If A and B, which are the bounding boxes in this contribution, match perfectly, the GIoU is $= 1$. The confidence of the network is divided by the confidence of the reference for evaluation, so a value of > 1 means that the confidence is higher than the reference. Since both criteria describe different aspects of an object detection, both are measured and evaluated separately and not combined into a single metric since the individual weighting of the criteria would be subjective.

The reference is the quality of object detection, when the matrix headlamp produces a high beam illumination. The utilization of the pixels of the matrix headlight is calculated by minimizing the Root Mean Squared Error (RMSE) between the matrix intensity distribution and a high beam pattern currently used in the premium segment. Fig. 3a shows these reference illuminations as well as the bounding boxes and object detection reliability with the YOLOv5 network of a vehicle at $\boldsymbol{p}_{100,3.5}$ and a pedestrian at $\boldsymbol{p}_{50,-2.5}$.

The first experiment investigates whether a selective uniform increase of illumination for the whole area of potentially relevant objects improves their detection when the environment is minimally illuminated. The minimum illumination level is shown in fig. 3b. Another aspect is to evaluate whether and to what extent other illumination features such as GFHB interfere with and affect object detection. For vehicles, GFHB is activated to prevent illumination of the upper part of the vehicle and for people to prevent illuminating their heads. GFHB and marker lights are active, so that the person's head is not illuminated and the position is highlighted with a projected line of matrix headlights from the ego vehicle to the pedestrian, which is intended to warn the human driver and direct his attention to potential dangerous spots. Fig. 5 shows a scenario with activated lighting functions.

Fig. 5: Visualization of a selectively illuminated red vehicle at position $\boldsymbol{p}_{100,3.5}$ with GFHB and blue person at location $\boldsymbol{p}_{50,-2.5}$ with GFHB and marker light. The class, confidence and bounding boxes of the YOLOv5 [9] object detection are also shown.

The first test scenario consists of detecting an oncoming red vehicle at the location $\boldsymbol{p}_{100,3.5}$, which covers the smallest number of pixels in the camera image compared to closer test positions and is therefore more difficult to detect. In the area of the vehicle, i.e. within its minimum enclosing bounding box, the target light intensity is uniformly set with SSC and the effects of confidence and GIoU are measured. The pixel utilization is increased from 0% to 100%. The results are shown in fig. 6 and compared with the baseline obtained by the unchanged minimum illumination (dotted lines). The reference is always high beam illumination. All experiments are repeatable, but for relative confidence and GIoU deviations of $\approx \pm 0.01$ occur. One possible reason would be stochastic lighting calculations in the ray tracing and antialiasing techniques of the Unreal Engine, but these variations require more investigation. In addition, the results depend on the color and material properties of the objects and especially on the design of the background, e.g. the presence

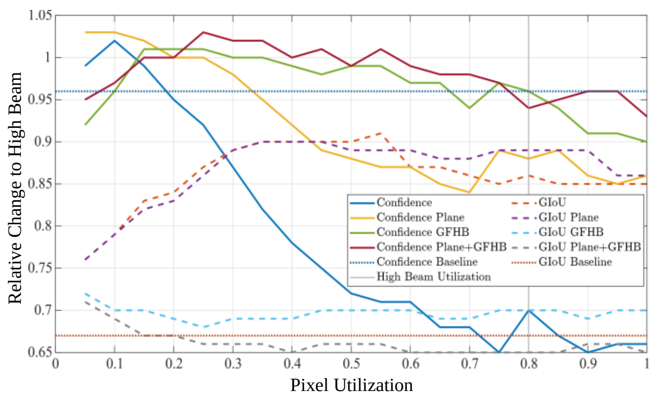


Fig. 6: Influence of changing utilization (1 = 100%) of the pixels, which illuminate a vehicle at $\boldsymbol{p}_{100,3.5}$, on the confidence and the GIoU under consideration of the GFHB lighting function. No line means no detection.

of trees. The exact influence of these parameters was not investigated, but the main general statements and conclusions of this contribution were empirically tested and confirmed with variable parameters.

If the vehicle is not illuminated at position $\boldsymbol{p}_{100,3.5}$, it will not be detected by the network. Low illumination increases confidence and GIoU, but high illumination decreases confidence and does not improve the GIoU (as shown in fig. 6 with the red dashed and blue solid lines). This is potentially caused by the appearance of the vehicle as a "flat" white object when the illumination is too high. In general, selectively increasing uniform illumination can improve object detection, but there is a threshold above which increasing the intensity no longer improves detection. Similar to the legibility of traffic signs, results can degrade if the illumination intensity is too high. When projecting a plane in the lateral direction at the position of the human driver of the oncoming vehicle with uniform illumination in the height and width of the vehicle as opposed to using a target cuboid as a primitive, the sides of the vehicle are not illuminated as much as when using a cuboid as a primitive. This results in a smoother drop in confidence as illumination increases, but the curve of GIoU remains unchanged (as shown in fig. 6 with the yellow and purple lines). Since the target area is smaller, the projected plane approach requires less energy than the cuboid and yields better results.

An important question for road safety is whether lighting functions could influence and interfere with object detection. To answer this question, GFHB is activated so that the upper part of the vehicle is not illuminated, and the experiment is repeated. The results in fig. 6 show that selectively illuminating the lower part of the vehicle improves detection confidence, but not GIoU, and using a box or plane as a target has no effect. The GIoU with GFHB is always lower, because the upper part of the vehicle is not visible in the captured image.

The next test scenario consists of improving the detection of the half-illuminated person at position $\boldsymbol{p}_{50,-2.5}$ by selectively illuminating the entire body. Using a projected box or plane as the uniform target primitive makes no difference in this case, so a comparison is not shown in fig. 7. Once the body is fully illuminated, the confidence increases and is higher at low illumination than at high beam and decreases as illumination increases, but the GIoU remains constant and is worse than at high beam (as shown in fig. 7 with the blue and red lines). The bounding box is higher than the reference, possibly caused by the illuminated tree in the background. As illuminance increases, the person appears uniformly white

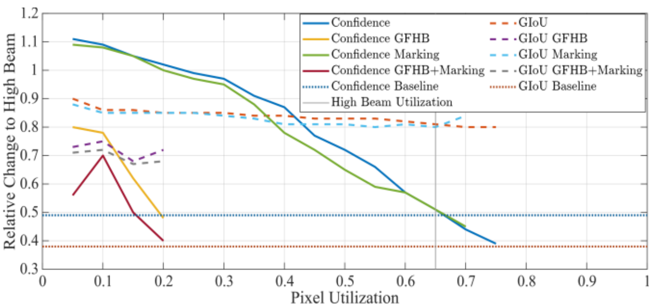


Fig. 7: Influence of changing utilization (1 = 100%) of the pixels, which illuminate a person at $\boldsymbol{p}_{50,-2.5}$, on the confidence and the GIoU under consideration of the GFHB lighting function. No line means no detection.

and at high illuminance the person is no longer detected as a false negative (as shown in fig. 7 with the disappearing lines). Too much illumination is thus critical to safety here, as it not only dazzles the pedestrian, but also interferes with or prevents object detection by the ego vehicle.

To avoid pedestrian dazzle, GFHB can be activated so that the person's head is not illuminated (as shown in fig. 5). Activating GFHB for pedestrians degrades the results and leads to an earlier false-negative result (as shown in fig. 7 with the yellow and purple lines). To warn the human driver during semi-automated or cooperative driving and draw the drivers' attention, a line from the vehicle to the person could be projected with the headlamps. If the line is bright and clearly visible from beginning to end, the illuminated person was not detected by the YOLOv5 network. A possible explanation is that the white line and the white person were combined by the network to form a new unknown object that was not present in the training dataset and thus could not be detected. With a line fading with increasing distance to the ego vehicle, as in fig. 5, the person is recognizable to YOLOv5 and the results are slightly worse than without a projected line. Thus, for line projection, it is recommended to use lines that end well before the object to avoid unintended links. Additionally, when using a minimal base illumination, projected symbols are better visible, because the positive contrast of the bright symbol to the dark road is higher. This can lead to unintended links for machine vision and to false interpretations, when the symbols such as lines are considered part of the road marking. An example therefore is fig. 6, where the projected line has a similar color and brightness as the road markings. The combination of marker line and GFHB yields the worst results in these test cases (as shown in fig. 7), but as long as the person is recognized, they are better than the baseline.

The novel minimum basic illumination with one illuminated object consumes only about $0.08 - 0.25 \cdot 0.08 + 0.1 \cdot 1 = 16\%$ of the energy of a normal high beam. The first term 0.08 is the general energy reduction e_{r} to 8% of the default high beam brightness for the used test scenario (as shown in fig. 3b). For this calculation, it is assumed for simplification, that the consumed energy is proportional to the luminous flux of the headlamp. The second term is the multiplication of the approximated relative area a_{z} in the headlamp beam pattern at full deactivation, which is in this case 25% = 0.25, with e_{r} to take the total deactivation of the illumination into account. The third term is the multiplication of the approximated relative area $a_{\mathrm{o},i}$, which the i-the object covers, is assumed to be 10% on average of the headlamp beam pattern, with energy consumed by the illumination in the area of the object. The chosen utilization and energy consumption $e_{\mathrm{o},i}$ in the area of the i-th object is assumed to be equal to high beam, so $e_{\mathrm{o},i}$ is 100% = 1. This is a worse case calculation, because good utilization in subjective opinion would be below high beam in all test cases. The high beam utilization in the area of the object is shown in all figures as a small gray vertical line. In general, the energy saving potential in a scene could be calculated with

$$e_{\mathrm{r}}\,(1 - a_{\mathrm{z}}) + \sum_{i=0}^{i=N-1} a_{\mathrm{o},i}\, e_{\mathrm{o},i}\,, \qquad (2)$$

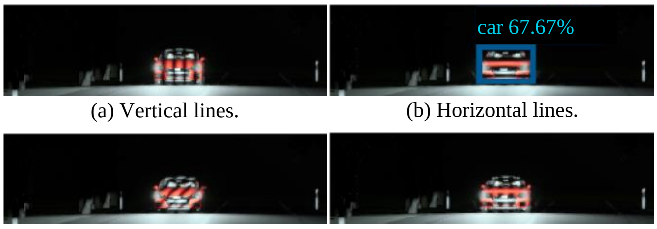
where N is the total number of illuminated traffic objects.

This is only a rough calculation to illustrate the potential of this concept, and the values will be further explored in an extended study with multiple traffic scenarios in future work.

In summary, selective illumination of traffic objects can improve the confidence of object detection to values higher than using high beam and a GIoU of about 0.85 can be achieved, but high illumination levels can degrade the results and lead to false negatives. In addition, lighting functions that were not taken into account during the training of the network can lower the quality of the detection and can produce false negatives as a worse case, where the object is no longer seen.

IV. SYMBOL PROJECTION FOR OBJECT DETECTION

Modern HD matrix headlights can project arbitrary images, so-called symbols, onto the road surface and objects. This is used for human-machine-communication between the automated vehicle and persons, which can be the driver or pedestrians. For the driver, the symbols are some kind of an in world head-up-display and for pedestrians they act like a messenger system. Knowing the ideal symbol's appearance and comparing it with its look in the camera image, the object's shape can be reconstructed in a kind of a 3D scan. This approach is called structured light and a commonly used pattern is parallel stripes, from whose deformation the surface can be reconstructed. To investigate the effect of structured light symbols on object detection algorithms that are not designed to process structured light, in the next experiment various symbols are projected onto the vehicle at position $\boldsymbol{p}_{100,3.5}$. The symbols evaluated are vertical and horizontal lines, lines rotated by 45° and crossing lines, which are shown in fig. 8. Here the patterns are projected on a red vehicle and change the subjective appearance of the vehicle in combination with the dark background.



(a) Vertical lines. (b) Horizontal lines.

(c) 45° rotated lines. (d) Crossing lines.

Fig. 8: Projection of different structured symbols on a red vehicle at $\boldsymbol{p}_{100,3.5}$. The class, confidence and bounding boxes of the YOLOv5 [9] object detection are also shown.

The object detection results, when the symbols are projected on the whole vehicle, are shown in fig. 9. The results depend on the relative size of the symbol to the object, but in general the quality of detection of non-optimized algorithms with structured light is worse than without. Here, the uniform plane illumination is the baseline (dotted lines). The vehicle can be detected at zero utilization with the 45° rotated lines (as shown in fig. 9 with the green and light blue lines) because the primitive is rotated by SSC by 45°, so that the lower side parts are minimally illuminated (as shown in fig. 8c), which seems to be sufficient for detection. The use of structured light leads to false-negative results (as shown in fig. 9, where the lines end), which means that the objects are not detected by the automated vehicle. This was also investigated with a pedestrian at position $\boldsymbol{p}_{50,-2.5}$, which led to similarly poor and safety-critical results, because the pedestrian was also not detected in the majority of test cases. A possible explanation is that the contrast of the lines and the area in between, in which the headlamp pixels are totally deactivated, is too high. The area between the stripes is too dark and blends with the dark background, which disturbs the outer shape of the objects and can be seen in fig. 8, so that the YOLOv5 cannot reconstruct the outer shape of the object, which leads to a false negative detection, because the vehicle is not recognized as a vehicle.

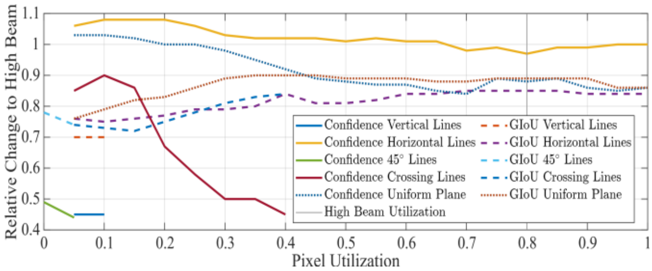


Fig. 9: Influence of changing utilization (1 = 100%) of the pixels, which illuminate a red vehicle at $\boldsymbol{p}_{100,3.5}$, on the confidence and the GIoU with different structured light, that consists of projected line symbols. No line means no detection.

Another approach is to not use uniform symbols as in section III, but to use randomized images $I \in \mathbb{R}^{n\times n}_{\geq 0 \wedge \leq 1}$ with n rows and n columns as patterns. The pixels of I are randomly set between 0 and 1 as real numbers. Projected patterns I with pixel values from a uniform distribution with a mean $\mu = 0.5$ and from a normal distribution with a mean $\mu = 0.5$ and a standard deviation $\sigma = 0.13$ are evaluated. The values of the symbol I are multiplied by SSC with the target pixel utilization to calculate the actual pixel utilization, so that these randomized symbols are on average half as bright as the uniform ones in section III, because they have a mean of $\mu = 0.5$. Fig. 10 shows the results for detecting a vehicle at $\boldsymbol{p}_{100,3.5}$ and fig. 11 shows the results for detecting a person at $\boldsymbol{p}_{50,-2.5}$.

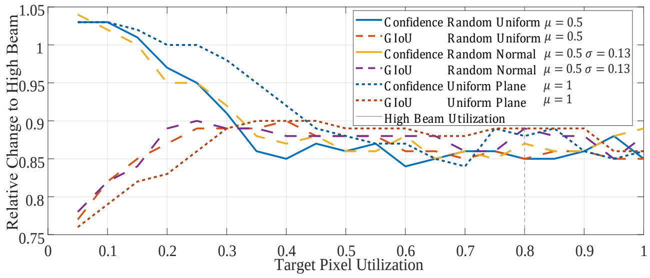


Fig. 10: Influence of changing utilization (1 = 100%) of the pixels, which illuminate a vehicle at $\boldsymbol{p}_{100,3.5}$, on the confidence and the GIoU with different projected random noise symbols. No line means no detection.

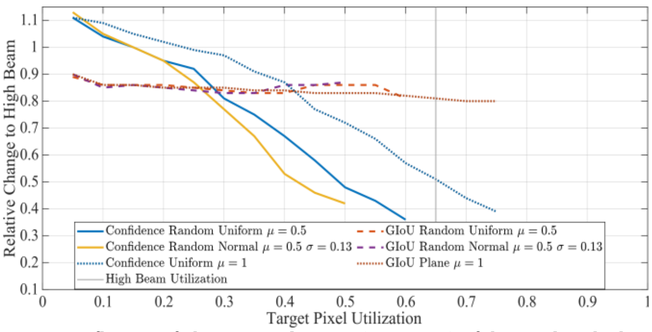


Fig. 11: Influence of changing utilization (1 = 100%) of the pixels, which illuminate a person at $\boldsymbol{p}_{50,-2.5}$, on the confidence and the GIoU with different projected random noise symbols. No line means no detection.

Using a uniform or normal distribution produces the same results with confidence lower or similar to projecting a uniform plane with μ = 1 and σ = 0.0. One possible explanation is that the inhomogeneous illumination disturbs the YOLOv5 network rather can making the shape more visible. The GIoU is similar, but the loss of the person detection starts at a lower pixel utilization. Since μ of the random images is half of the uniform images, the projection of these images consumes on average half the energy as the uniform images. Therefore, for a comparison at the same energy consumption, the results of the random images should be compared with those of the uniform image at half the pixel utilization. The comparison of fig. 10 and fig. 11 leads to a worse confidence, but a similar or better GIoU for the random images. In summary, this means that if the main task is to determine the class of objects, it is energetically more optimal to use a uniform target distribution, but if the task is to obtain an accurate bounding box, a random distribution could improve the results as long as the loss of confidence is acceptable. Structured light, however, should generally be avoided in the context of non-optimized networks, as false negatives can occur.

V. CONCLUSION & OUTLOOK

The contribution at hand presents a novel approach to dynamic, energy-optimized illumination by matrix headlights for automated driving that achieves a similar quality of automatic object detection as high beams and requires only about ≈16% of the energy in the evaluated test scenario. The proposed uniform illumination strategy has been compared with alternatives such as structured light and has the best overall quality and does not produce false negative object detection results. So the novel approach of using a minimal base illumination in combination with a dynamic adjustment strategy, which will be developed in a further contribution, seems to be promising for energy-efficient and sustainable electrical vehicles. However, other illumination functions interfere with object detection and projected symbols should be separated from the target object to avoid false negative results, which was investigated using marker lights and pedestrians as examples.

This contribution is only the first step in the development of dynamic and in the loop-controlled illumination for optical sensors and machine vision and has shown the feasibility and energy saving potential. All evaluations were performed in simulation, so the next step would be to use existing real matrix headlights such as [15] to replicate the experiments in reality and validate and optimize the results. Moreover, the evaluation was performed with a single scenario, so another next step will be to define a realistic set of typical scenarios, such as cities, country roads or highways, and evaluate the energy saving potential in these scenarios and additionally the collaboration with other objects, such as street lamps.

REFERENCES

[1] A. Erkan, K. Kosmas, J. Kobbert, and T. Khanh, “Energy saving potential of headlights by determining the current utilization rate of headlight functions,” 13th International Symposium on Automotive Lightning – ISAL 2019, 2019.
[2] C. Schmidt, M. Niedling, and W. Kösters, “Sustainable vehicle lights,” 14th International Symposium on Automotive Lightning – ISAL 2021, 2022.
[3] AUDI AG (Ed.), “Audi A8 – Digital Matrix LED and digital OLED technology,” 11/2021, accessed: 2022-05-24. [Online]. Available: https://www.audi.com/en/innovation/e-mobility/matrix-led-headlights.html
[4] B. Hummels, “Blendfreies Fernlicht,” Ph.D. dissertation, Universität Karlsruhe (TH), 2009.
[5] T. Q. Khanh and J. Kobbert, Automotive Front Lighting System (Status 2020). Springer Berlin Heidelberg, 2020. [Online]. Available: https://doi.org/10.1007/978-3-642-27851-8_427-1
[6] M. Waldner and T. Bertram, “Feedforward Control of HD-Headlights for Automated Driving,” 14th International Symposium on Automotive Lighting – ISAL 2021, 2022.
[7] N. Alarcon, “See theLight: DNN-based Perception for Automatic High Beam Control,”2020, accessed:2022-05-24. [Online]. Available: https://developer.nvidia.com/blog/dnn-based-perception-for-automatic-high-beam-control/
[8] S. Parvin, M. Islam, L. J. Rozario, et al., “Nighttime Vehicle Detection Methods Based on Headlight Feature: A Review.” IAENG International Journal of Computer Science, vol. 49, no. 1, 2022.
[9] G. Jocher, A. Chaurasia, A. Stokenother., et al., “ultralytics/yolov5: v6.1 TensorRT, TensorFlow Edge TPU and OpenVINO Export and Inference,” 2022. [Online]. Available: https://doi.org/10.5281/zenodo.6222936
[10] D. Hoffmann, A. Erkan, T. Singer, and T. Q. Khanh, “Investigation of different influencing parameters on the quality of object detection by camera systems in highly automated vehicles,” 14th International Symposium on Automotive Lightning – ISAL 2021, 2022.
[11] H. Rezatofighi, N. Tsoi, J. Gwak, A. Sadeghian, I. Reid, and S. Savarese, “Generalized Intersection over Union: A Metric and A Loss for Bounding Box Regression,” The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2019. [Online]. Available: https://giou.stanford.edu/
[12] C. Wilks and B. Kubitza, “Next lighting generation: From static light pattern to light movies,” SIA VISION 2016, 2016.
[13] T. Singer, A.Erkan, J. Willmann, D. Hoffmann, and T. Q. Khanh, “Photometric Characterization and Evaluation of Head-Mounted-Displays for Virtual Night Driving,” 14th International Symposium on Automotive Lightning – ISAL 2021, 2022.
[14] M. Waldner, N. Müller, and T. Bertram, “Flexible Modeling of High-Definition Matrix Headlights,” IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM) 2022, 2022.
[15] M. Kleinkes, W. Pohlmann, and C. Wilks, “SSL|HD – High Tech Light for new safety & comfort functions,” 14th International Symposium on Automotive Lightning – ISAL 2021, 2022.
[16] M. Waldner and T. Bertram, “Simulation of High-Definition Pixel Headlights,” 15th International Symposium on Visual Computing, 2020.
[17] N. Bell and M. Garland, “Efficient Sparse Matrix-Vector Multiplication on CUDA,” 2008. [Online]. Available: https://www.nvidia.com/docs/IO/ 66889/nvr-2008-004.pdf
[18] N. Bell and M. Garland, “Implementing Sparse Matrix-Vector Multiplication on Throughput-Oriented Processors,” Proceedings of the Conference on High Performance Computing Networking, Storage and Analysis, 2009. [Online]. Available: https://www.nvidia.com/docs/IO/77944/ sc09-spmv-throughput.pdf
[19] M. Waldner and T. Bertram, “Virtual Evaluation of High-Definition Lighting Functions for Various Beam Patterns for Rapid-Prototyping,” Lux junior 2021: 15. Internationales Forum für den lichttechnischen Nachwuchs, 2021. [Online]. Available: https://www.db-thueringen.de/receive/dbt_mods_00048427
[20] B. Seiser, “Improving Visibility with DLP® Headlights,” 2020, accessed: 2022-06-08. [Online]. Available: https://www.ti.com/lit/wp/slyy201/ slyy201.pdf