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Concept of a Matrix Headlight Control Loop for Enhanced Object Detection in Automated Driving

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Abstract

The contribution at hand proposes a novel concept of a control loop for matrix headlights so that the illumination of the environment is varied to enhance the detection of objects for computer vision while considering a trade-off with the headlight energy consumption. The definition of the control error is especially discussed since one challenge of the control loop lies within the combination of object detection quality and energy consumption, which shall represent desired behaviors in each situation. Different control errors are proposed, and their advantages and disadvantages are evaluated in simulation.

Index Terms: Matrix Headlights, Object Detection, Control, Simulation

1 Introduction

The safety of automated driving depends on a correctly perceived environment. The ego vehicle uses sensors like optical cameras to get information about the surroundings and detect objects with computer vision algorithms. With the camera information, it is possible to detect objects like vulnerable road users, e.g. pedestrians, to avoid accidents. However, camera detections are often only accurate and reliable in good lighting conditions since the camera suffers from poor lighting.

Therefore, the general idea is to support the camera with a dynamic illumination of matrix headlights to enhance object detection in bad lighting situations. With the individual control of single light sources of the matrix headlight called pixels, parts of the environment can be selectively illuminated. Thus, for example, better contrasts of traffic objects can be created for better object detection.

Previous work [1] has shown that today's matrix headlight distributions are inefficient for computer vision at night. One new lighting distribution suited for automated driving uses the selective illumination of matrix headlights to illuminate each material in the environment with a different luminous intensity called material intensity, creating a material-based illumination [2]. The basis for such a material-based illumination is shown in Fig. 1, where an HD map of a real environment in the German city Lippstadt is distinguished into 19 different materials. Each of these materials can be illuminated with a different material intensity so that, e.g., the asphalt can be illuminated brighter than the roof tiles of the houses. In this way, the different reflective behaviors or colors of materials can be used to avoid overexposed images or refine the contrast of objects to their environment. Previous work has shown that material-based illumination improves computer vision quality and saves energy simultaneously [1,3]. However, the optimal material intensities with which the materials are illuminated vary among different situations, making it difficult to find general laws for determining the optimal material intensities to enhance the detection quality for computer vision for each situation while considering low energy consumption.

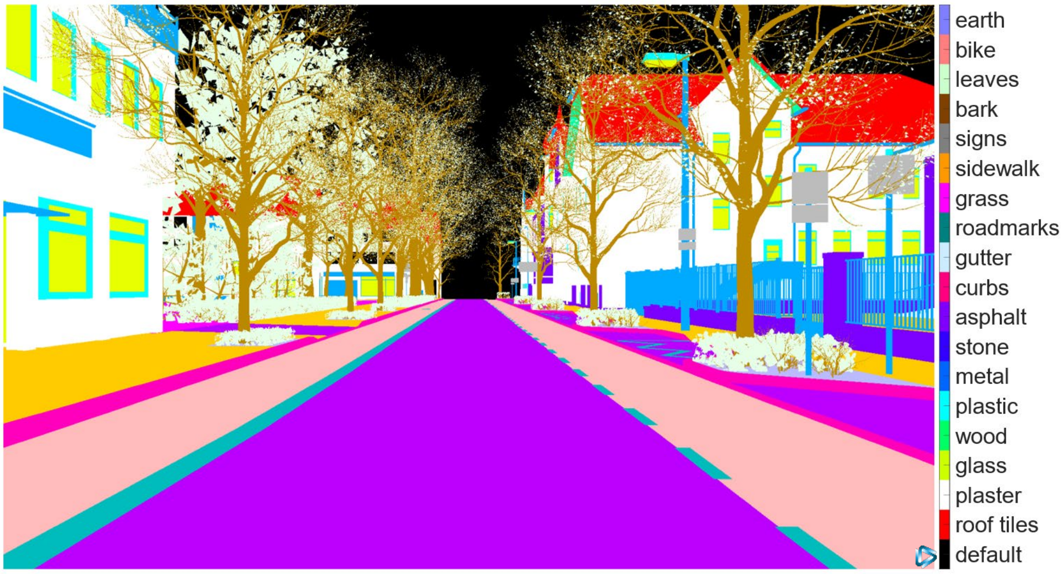


Fig. 1: 3D environment model with 19 different color-coded materials according to the color bar on the right.

The determination of the optimal material intensities requires an optimization process. Regardless of the optimization algorithm used, this optimization process is not capable of real-time, especially because the detection quality costs are defined by the output of a neural network, which makes the cost function discontinuous and non-differentiable. Therefore, it is only possible to investigate multiple scenarios beforehand, either in simulation or, with much more effort in reality, to find a compromise for the material intensities that perform the best among those multiple scenarios and to apply them in a moving vehicle statically. This is not desirable since unknown situations might occur where the beforehand determined material intensities perform poorly, even to such an extent that they might worsen the detection quality of computer vision, creating dangerous situations with non-detected traffic-relevant objects that could lead to an accident.

The contribution at hand addresses this problem by proposing a novel concept of a control loop for the material intensities, which can adjust the light distribution of the matrix headlights dynamically and is thus, in principle, real-time capable and applicable in real driving vehicles with the usage of [4]. This contribution focuses on defining the control error composed of the reference value and the measured output of the sensor system. The challenge is to achieve the desired behavior of obtaining the best trade-off between high detection quality and low energy consumption while all situations are represented correctly by the measured output and the control error. The more energy is consumed, the more the control error should deviate from zero, and the worse the detection quality becomes, the more it should also deviate from zero.

In Section 2, the concept of the matrix headlight control loop will be presented. Section 3 discussed different possibilities for defining the control error, the measured output, and the reference value. In Section 4, the different control errors will be analyzed and evaluated, followed by the conclusion and outlook in Section 5.

2 Control Loop Concept

The design of the matrix headlight control loop is based on the previously used optimization loop from [3], which is shown in Fig. 2. Some of the blocks are therefore similar to the control loop illustrated in Fig. 3. The control loop is a time-discrete digital control loop since the measured output can only be retrieved for a particular illumination by the matrix-headlights. As mentioned in Section 1, the neural network output used for the evaluation of computer vision is discontinuous and non-differentiable, making it possible only to retrieve the detections at time-discrete steps, the current timestep being k. In the following section, the functionality of the control loop and its components will be explained further.

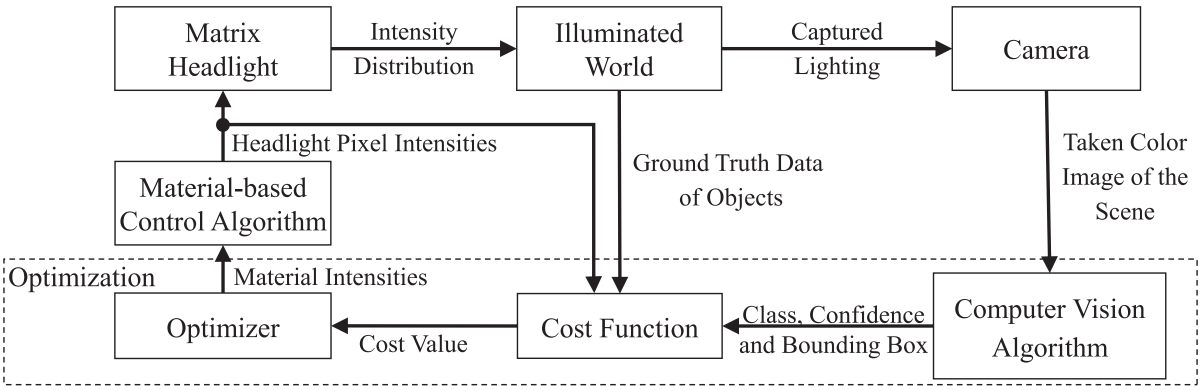


Fig. 2: Matrix headlight optimization loop for material intensities [3].

The reference value of the control loop is compared with the measured output, that is output by the sensor and the subsequent data processing chain. By this comparison, the control error e_k of the k-th timestep is calculated. The control error is the controller input, consisting of two major blocks. Based on the derived control error, the first block adjusts the material intensities with a PID controller. Since there are a number of n_m

material intensities according to the number of distinguished materials in the environment, the parameter vectors of the PID controller must also have the same dimension, e.g. a proportional gain $k_{\mathrm{p},i}$ for each material with the index i, creating a vector of $\boldsymbol{k}_{\mathrm{p}} \in \mathbb{R}^{n_{\mathrm{m}}}$. The same goes for the integral gain $\boldsymbol{k}_{\mathrm{i}} \in \mathbb{R}^{n_{\mathrm{m}}}$ and differentiae gain $\boldsymbol{k}_{\mathrm{d}} \in \mathbb{R}^{n_{\mathrm{m}}}$. Otherwise, each material intensity cannot be controlled individually, which neglects the sense of the material-based illumination, leading to a homogenous illumination where each material has the same material intensity. In contrast to one controller for all material intensities with vectorial gains, it is also possible to create several n_{m} parallel control loops with a common control system plant. Despite the common plant, the system could also defer in the measured output and thus the control error. However, a system with multiple parallel control loops will not be the focus of this contribution.

The respective outputs of the single parts of the PID controller consisting of the P-output $\boldsymbol{y}_{k,\mathrm{p}} \in \mathbb{R}^{n_{\mathrm{m}}}$, the I-output $\boldsymbol{y}_{k,\mathrm{i}} \in \mathbb{R}^{n_{\mathrm{m}}}$ and the D-output $\boldsymbol{y}_{k,\mathrm{d}} \in \mathbb{R}^{n_{\mathrm{m}}}$ for the k-th timestep are

$$\boldsymbol{y}_{k,\mathrm{p}} = \boldsymbol{k}_{\mathrm{p}} e_k \tag{1}$$

$$\boldsymbol{y}_{k,\mathrm{i}} = \boldsymbol{y}_{k-1} + \frac{e_k}{\boldsymbol{k}_{\mathrm{i}}} \Delta T \tag{2}$$

$$\boldsymbol{y}_{k,\mathrm{d}} = \frac{e_k - e_{k-1}}{\Delta T} \boldsymbol{k}_{\mathrm{d}}, \tag{3}$$

With the duration of the discrete timestep ΔT and the overall limited output $\boldsymbol{y}_k \in \mathbb{R}^{n_{\mathrm{m}}}_{\geq 0 \wedge \leq 1}$ of the controller, that is the sum of the single outputs

$$\boldsymbol{y}_k = \boldsymbol{y}_{k,\mathrm{p}} + \boldsymbol{y}_{k,\mathrm{i}} + \boldsymbol{y}_{k,\mathrm{d}}. \tag{4}$$

The values of $\boldsymbol{y}_k$ are the material intensities for each material and must only be between 0 and 1 since these are the respective minimum and maximum values for the luminous intensity, representing 0% to 100% of the maximum possible luminous intensity of the headlight. The duration of the timestep ΔT is dependent on the time it takes to once run through the control loop chain. That means it is based on the time it takes to determine the pixel luminous intensity vector $\boldsymbol{I}_{\mathrm{v}} \in \mathbb{R}^{n_{\mathrm{p}}}_{\geq 0 \wedge \leq 1}$ of the n_{p} pixels of the matrix headlight by the material-based control algorithm, the time for applying the new illumination on the matrix headlights, the time for the camera to capture an image, and the subsequent computer vision processing time, the time for determining the measured output and retrieving the control error.

The second block of the controller in the control loop is the material-based algorithm, which calculates based on the output of the PID controller $\boldsymbol{y}_k$, the individual material intensities and with that $\boldsymbol{I}_{\mathrm{v}}$ of the matrix headlight, which is the control variable of the system. The algorithm is described in detail in [2]. $\boldsymbol{I}_{\mathrm{v}}$ is the input for the control system plant, which consists of the matrix headlight, which projects its luminous intensity distribution into the simulated or real world. The luminous intensity distribution is determined by $\boldsymbol{I}_{\mathrm{v}}$. The output of the control system plant is the illuminated world, which is also the overall system output.

The system output is fed back with a feedback loop consisting of a sensor and data processing block that determines the measured output. In general, the sensor and data processing block evaluate the detection quality of a computer vision algorithm that is achieved with the current illumination of the world. Additionally, it assesses the energy consumption of the matrix headlights and combines these two criteria to determine the measured output. In detail, the camera captures a color image of the illuminated world that is fed into the computer vision algorithm. The computer vision algorithm outputs information regarding the detected objects in the camera image, namely the class, the confidence, the position in the image, and the bounding boxes of the detected objects. This information is analyzed to evaluate the detection quality and, thus, the detection costs. With the known $\boldsymbol{I}_{\mathrm{v}}$ of the matrix headlight, the energy consumption of the matrix headlight can be calculated, representing the energy costs for the current illumination. Both the detection and energy costs are combined to form the weighted, measured output, which is compared to the reference value, closing the loop. The loop with all component blocks is shown in Fig. 3.

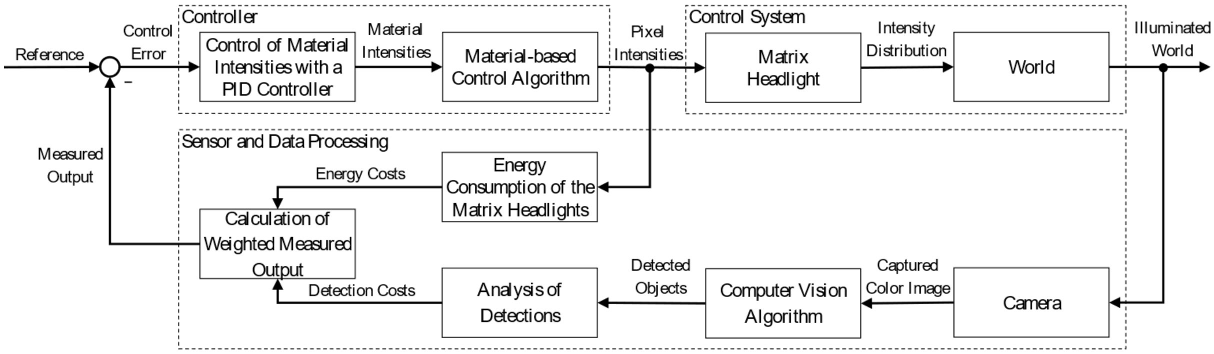


Fig. 3: Matrix headlight control loop for material intensities.

3 Definition of the Control Error

The main challenge for the creation of the matrix headlight control loop is the definition of the control error e and, therefore, also the definition of the measured output and the reference. According to Section 2, the measured output comprises energy and detection costs. These two are combined and weighted to form the measured output. For simplicity, in this contribution, the two terms are equally weighted, and the number of objects to be detected is also not included and, therefore, fixed to one object. Moreover, the costs for the quality of detection $c_{\mathrm{q}} \in \mathbb{R}_{\geq 0 \wedge \leq 1}$ [5] is only considered to represent the quality of confidence. The energy costs are $c_{\mathrm{E}} \in \mathbb{R}_{\geq 0 \leq 1}$ [5]. In future work, the detection term should be weighted at 80% and the energy term at 20% since the primary purpose of automotive headlights is to enhance the vision quality. The number of objects to be detected must also be considered, as higher energy consumption should not be penalized more when there are several objects. The aim for the definition of the control error is to find an e, that can represent every situation correctly, e.g., that the more energy is used, the more e deviates from zero, and the worse the detection quality, the more also should e deviate from zero.

There are multiple ways to combine the energy and detection into the measured output and thus into the control error with a corresponding reference value. Some of these possibilities will be discussed in this section. In the following, the reference value w for the controller is always $w = 0$, as the aim is to achieve costs of 0. The detection quality costs will be measured only by the confidences of the detected objects so c_q only considers the quality of confidences and not the detection rate and intersection over union as in [5]. The energy costs for the matrix headlight c_E are calculated as presented in [5].

Starting from the working cost function used for optimization in previous work [1,3], one way to define the control error is

$$e_0 = w - \left(0.5c_\mathrm{E} + 0.5c_\mathrm{q}\right). \tag{5}$$

Other possibilities for the calculation of the control error, which were found in successive empirical investigations to present a large variety, are

$$e_1 = w + (1 - c_\mathrm{E})c_\mathrm{q} = w + c_\mathrm{q} - c_\mathrm{q}\, c_\mathrm{E} \tag{6}$$

$$e_2 = w + 2 - 2c_\mathrm{E} - c_\mathrm{q} \tag{7}$$

$$e_3 = w + c_\mathrm{q} + c_\mathrm{E} \tag{8}$$

$$e_4 = w + c_\mathrm{q} - c_\mathrm{E} \tag{9}$$

$$e_5 = w + 1 - \frac{c_\mathrm{E}}{\max(1 - c_\mathrm{q}, 0.01)} \tag{10}$$

$$e_6 = w - \frac{c_\mathrm{E}}{\max\left(1 - c_\mathrm{q}, 0.01\right)} \tag{11}$$

$$e_7 = w + 1 - \frac{1 - c_\mathrm{q}}{\max(1 - c_\mathrm{E}, 0.01)} \tag{12}$$

$$e_8 = \begin{cases} w + c_\mathrm{q}\, c_\mathrm{E}, & \text{if } c_\mathrm{q} \neq 1, \\ -2, & \text{if } c_\mathrm{q} = 1 \end{cases} \tag{13}$$

$$e_9 = w + 1 - (1 - c_\mathrm{q})(1 - c_\mathrm{E}) = w + c_\mathrm{q} + c_\mathrm{E} - c_\mathrm{q}\, c_\mathrm{E}\,. \tag{14}$$

If the control error $e > 2$, then $e = 2$, and if $e < -2$, then $e = -2$ to limit the PID controller input since the control errors e_5, e_6 and e_7 could otherwise lead to high deviations from zero. The threshold of 2 is chosen since c_q and c_E are limited to $[0,1]$. High deviations cannot be realized regardless of the determined controller variables $\boldsymbol{k}_\mathrm{p}, \boldsymbol{k}_\mathrm{i}$ and $\boldsymbol{k}_\mathrm{d}$ when also small changes of e shall impact the material intensities, which are only in a range from 0 to 1.

One main issue is how to perform the combination of c_q and c_E, so that the control error can become both positive and negative depending on the reference. It is important that the control error can be both positive and negative because otherwise, the controller will only increase the material intensities or decrease the material intensities compared to the previous timesteps. It would not be possible to change the direction of the change in material intensities. Even though some of the proposed control errors do not allow for being both positive and negative, namely e_0, e_1, e_3, e_6, e_9. These are not canceled out since they yield other advantages, e.g., sudden peaks in confidence can be represented correctly, which is impossible with some of the other control errors.

Additionally, the challenge of defining the control error lies in how to consider the two terms of energy costs and detection costs sign-wise. From intuition, the energy costs should oppose the detection costs. The more energy is used, or the more pixels have a high luminous intensity, the better the detection quality should be. However, previous work [1-3] has also shown that increasing the pixel luminous intensity is not always beneficial since this can also worsen the detection results. So, to represent this behavior, assuming detection and energy as opposing factors from the beginning is not valid. The control errors e_2, e_3, e_4 suffer from this assumption that is not valid for every situation. These are also not canceled out because successive empirical investigations show that the assumption might be valid in most scenarios for specific luminous intensity ranges of the headlight.

There might also be other cases like the control errors e_2 and e_5, where the insertion of the optimal cost values of 0 for c_q and c_E does not lead to a control error of zero. However, depending on the design of the PID controller, the actual behavior represents the desired outcome of a compromise between low energy consumption and good detection quality.

Overall, none of the control errors above can probably represent every situation accurately and correctly. However, this list is incomplete, and other fitting control errors might exist. Alternatively, one solution to represent every situation could be combining several control errors or choosing the best fitting control error regarding a situation along a Pareto front. Another possibility for a dynamic control loop is a sort of sampling-based optimization, where the material intensities are increased and decreased, and based on the output, the change direction for the better trade-off between detection quality and energy consumption is determined.

4 Evaluation of Different Control Errors

The evaluation of the different control errors is done virtually in Unreal Engine 5.2 [6] with the headlight simulation model that was also applied in [1,3] and presented in [7]. For the illumination, a pair of high-definition matrix headlights with 640×160 pixels, amounting to a number of $n_\mathrm{p} = 102{,}400$ pixels, with an opening angle of $40°$ horizontal and $10°$ vertical is used. The opening angle is derived from the real Porsche headlamps in [8], and the pixel amount is similar to the amount used in previous publications [1-3]. In contrast to the previous work [1-3], the aspect ratio is now 4:1, like that of a real Porsche headlight [8].

The example scenario that will be investigated consists of one dark-dressed and thus more challenging to be-detected pedestrian at night and the virtual 3D environment of the real German city Lippstadt, in detail the street Woldemei leading from the train station Lippstadt to the north. The 3D environment was created by 3D Mapping Solutions. The pedestrian is placed 15 m in front of the ego vehicle. The scenario is shown in Fig. 4 with a homogenous light distribution at nighttime, where all pixel luminous intensities of $\boldsymbol{I}_\mathrm{v}$ are set to 0.3. The corresponding environment distinguished in 19 different materials is shown in Fig. 1.

(a) Illuminated scenario from the driver's perspective (b) Unlit overview of the scenario

Fig. 4: Evaluation scenario for the analysis of control error e. A black-dressed pedestrian crosses the street 15 m in front of the ego vehicle.

The focus of this contribution is to investigate whether the measured output and the defined control errors correctly represent the situation, namely that the deviation of e from zero should be higher when the detection quality worsens and the energy consumption increases. In this contribution, the controller will be neglected, and the pixel luminous intensities of $\boldsymbol{I}_\mathrm{v}$ will incrementally increase from 0 to 1 with steps of 0.01 in an open loop. The computer vision algorithm for the evaluation is YOLOv8 [9] since this is a state-of-the-art detection algorithm for color images of a camera. The algorithm is trained on the daytime COCO dataset without any further training. The desired detection quality with headlights should be like the detection during the day. The open loop with the pixel intensities $\boldsymbol{I}_\mathrm{v}$ as the input and the control error e as the output is shown in Fig. 5.

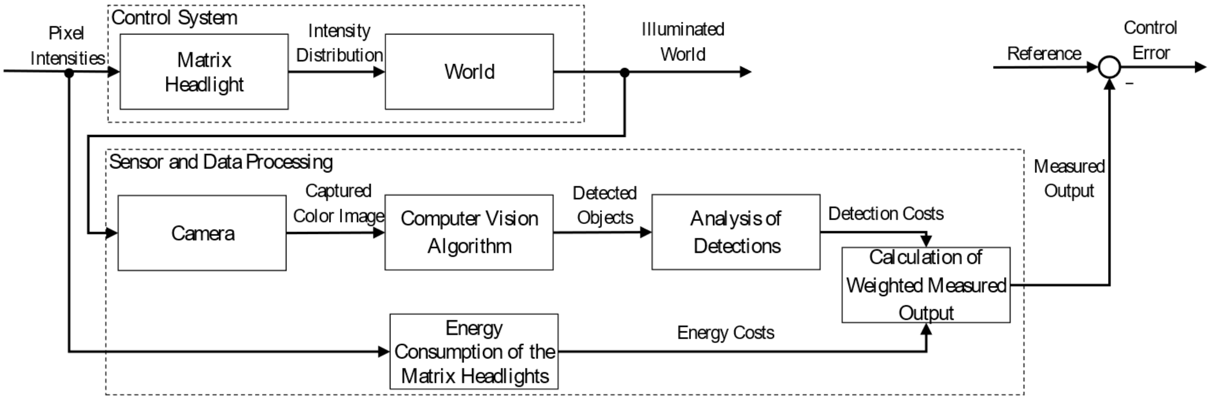
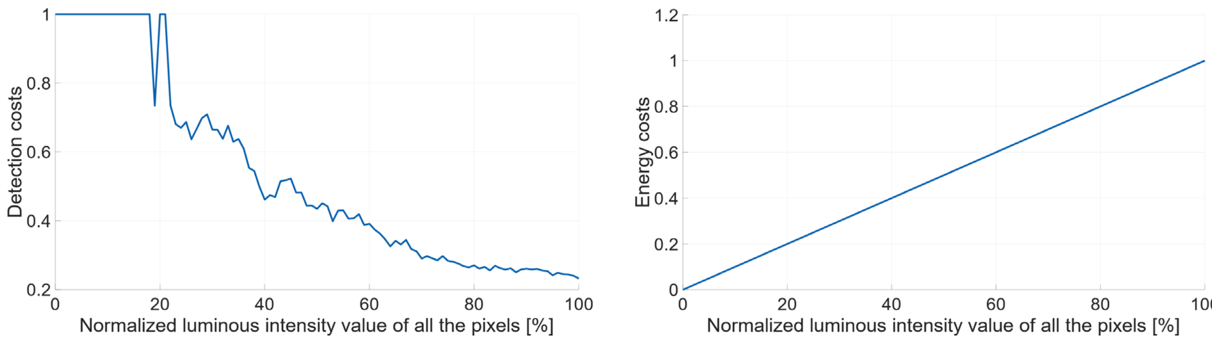


Fig. 5: Open loop without controller for analyzing the behavior of the control error e.

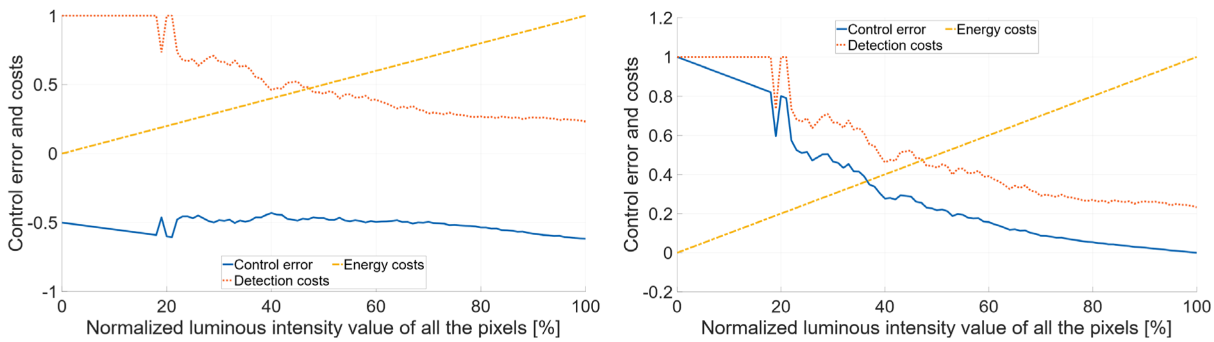
The detection quality c_q of the scenario, considering only the quality of confidence and depending on $\boldsymbol{I}_\mathrm{v}$, is shown in Fig. 6 on the left. The corresponding energy consumption graph is presented in Fig. 6 on the right.



(a) Detection costs depending on the luminous intensity (b) Energy costs depending on the luminous intensity

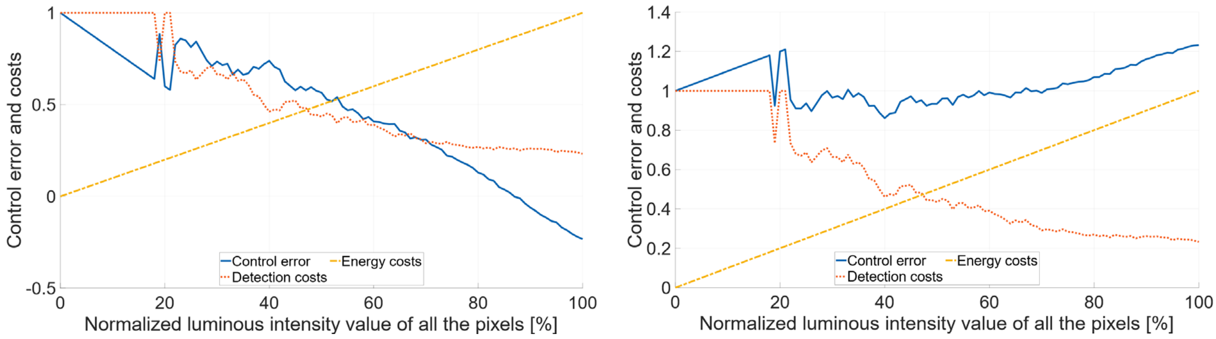
Fig. 6: Detection costs and energy consumption costs during the stepwise increase of the normalized luminous intensity value of all the pixels for the scenario in Fig. 4.

The corresponding graphs of the control errors e_0 to e_9 are shown in the following Figures 7-11 with the detection costs and energy costs graphs for reference.



(a) Behavior of e_0 (b) Behavior of e_1

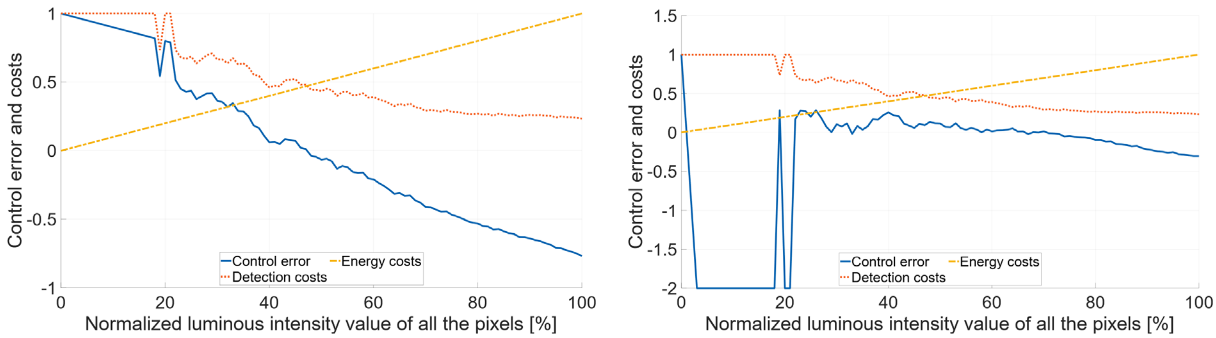
Fig. 7: Behavior of the control errors e_0 and e_1 during the stepwise increase of the normalized luminous intensity value of all the pixels for the scenario in Fig. 4.



(a) Behavior of e_2

(b) Behavior of e_3

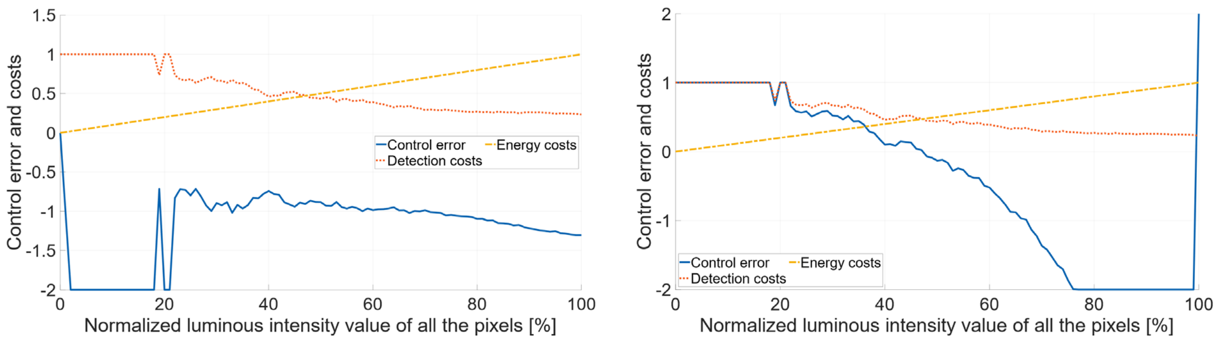
Fig. 8: Behavior of the control errors e_2 and e_3 during the stepwise increase of the normalized luminous intensity value of all the pixels for the scenario in Fig. 4.



(a) Behavior of e_4

(b) Behavior of e_5

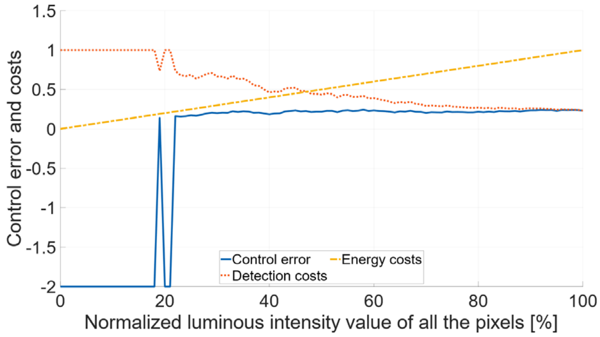
Fig. 9: Behavior of the control errors e_4 and e_5 during the stepwise increase of the normalized luminous intensity value of all the pixels for the scenario in Fig. 4.



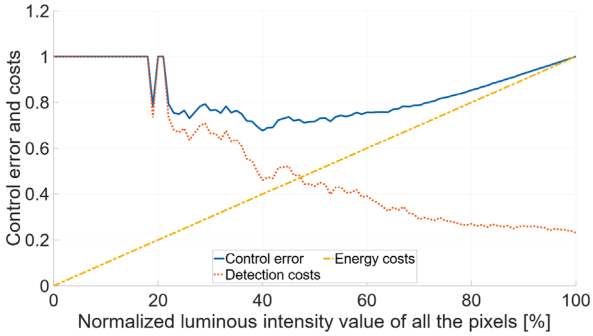
(a) Behavior of e_6

(b) Behavior of e_7

Fig. 10: Behavior of the control errors e_6 and e_7 during the stepwise increase of the normalized luminous intensity value of all the pixels for the scenario in Fig. 4.



(a) Behavior of e_8



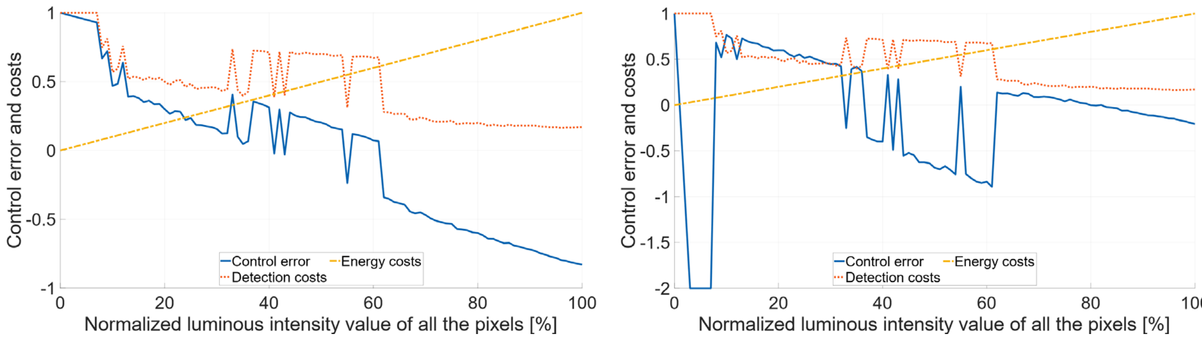
(b) Behavior of e_9

Fig. 11: Behavior of the control errors e_8 and e_9 during the stepwise increase of the normalized luminous intensity value of all the pixels for the scenario in Fig. 4.

As already mentioned in Section 4, some of the control errors suffer from the problem that they cannot be both positive or negative, like e_0, e_1, e_3, e_6 and e_9. Most of them do not even come close to an e of zero. e_6 approaches zero for no illumination and e_1 approaches zero for the maximum possible luminous intensity, which is not desirable. e_0 in Fig. 7a can map sudden confidence changes correctly without overshooting the border of zero. The same goes for e_1 in Fig. 7b. But in contrast to e_1, the minimum deviation of e_0 from zero might represent a desirable trade-off between the detection quality and energy consumption.

e_2 in Fig. 8a can become both positive and negative, but it does not map the change in confidence correctly, leading to a larger deviation of e_2 from zero with better detection quality and thus displays wrong behavior. Opposite to that, e_3 in Fig. 8b represents these changes correctly but suffers from being only positive. However, like e_0, the minimum deviation of zero might be a good trade-off between the criteria. e_4 in Fig. 9a can be both positive and negative, but it is still doubtful if $e_4 = 0$ is displaying the best compromise. Additionally, even if e_4 maps confidence changes correctly to a certain degree, it incorrectly maps the confidence when $e_4 < 0$. Then, an improvement in confidence leads to a larger deviation from zero for e_4. For a similar scenario with another pedestrian crossing the same street at a closer distance than in the focused scenario of this contribution, overshooting the border of $e_4 = 0$ is possible for e_4, although there is a confidence peak. This is shown in Fig. 12a, where the graphs for the energy consumption and the scenario-specific progress for the detection costs are illustrated additionally to the control error e_4.

e_5 in Fig. 9b is one of the control errors that can be both positive and negative. Because of the division, there are large fluctuations for $c_q = 1$, resulting in using the limits for the PID controller input of -2. The changes in confidence are not represented correctly, especially for $e_5 > 0$, since the deviation of e_5 from zero increases for better detection quality. Additionally, confidence peaks tend to overshoot the border of zero. These effects are also shown for the other scenario in Fig. 12b, which is the same scenario as for Fig. 12a.



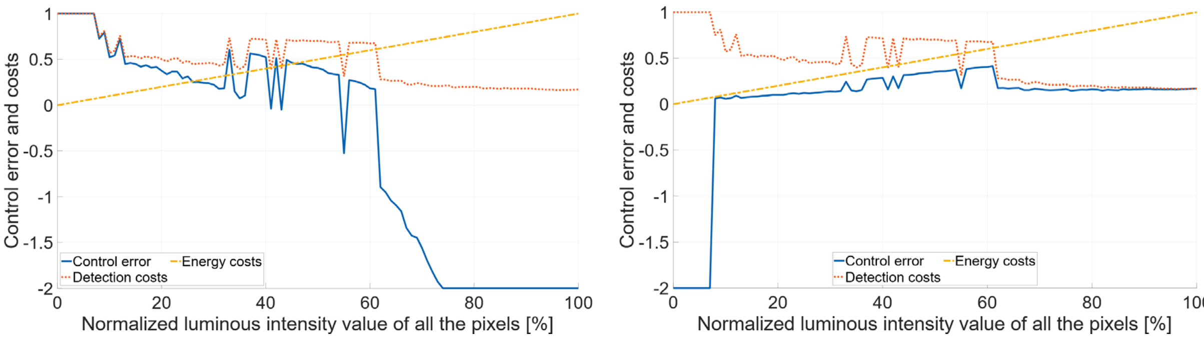
(a) Behavior of e_4, other scenario

(b) Behavior of e_5, other scenario

Fig. 12: Behavior of the control errors e_4 and e_5 during the stepwise increase of the normalized luminous intensity value of all the pixels for the similar scenario with another, closer pedestrian.

e_6 in Fig. 10a can only be negative, except for when the luminous intensities of all the pixels are zero. If a basic illumination is always assumed to be active for safety reasons, then this case can be ignored. Other than that, e_6 displays the change in confidence correctly and does not overshoot the zero border if there is a confidence peak. e_7 in Fig. 10b can become both positive and negative and maps changes in confidence correctly if $e_7 > 0$. However, for $e_7 < 0$, the mapping is incorrect, and confidence peaks can overshoot the border of zero. This is also emphasized by considering the graph of the other scenario, where there are more and larger confidence peaks, as shown in Fig. 13a. The sudden change in the control error for large luminous intensity around one can be ignored since these will not be applied due to cooling and degrading reasons of a matrix LED headlight. Because of that, there will be a limit on the output of the PID controller for the material intensities.

e_8 in Fig. 11a can be positive and negative, but only due to setting it statically to negative values if there is no detection. When inspecting the corresponding graphs in Fig. 11a and for the other scenario in Fig. 13b, this leads to sudden changes and large fluctuations of e_8. Although a positive and negative control error should be good in theory, in this case, it might be better to set e_8 to a positive value for correctly mapping of the detection costs without getting high confidence peaks, as in Fig. 11a. The other scenario compensates for this since it does not change between no detection and detection more than once. Nevertheless, e_8 maps the detection costs with possible confidence peaks correctly, not overshooting the border of zero when the static negative value settings are ignored.



(a) Behavior of e_7, other scenario

(b) Behavior of e_8, other scenario

Fig. 12: Behavior of the control errors e_7 and e_8 during the stepwise increase of the normalized luminous intensity value of all the pixels for the similar scenario with another, closer pedestrian.

e_9 in Fig. 11b cannot be negative, but it represents the detection costs correctly with its confidence peaks. The minimum deviation of e_9 from zero might be a desirable compromise between detection quality and energy consumption.

The evaluation shows that all the presented possibilities for defining the control error yield advantages and disadvantages. None of the control errors can be both positive and negative while also representing the detection costs and the confidence peaks correctly simultaneously. However, some control errors perform under certain conditions correctly and under other conditions not. Thus, there is the possibility of combining different control errors, e.g., defining e as e_4 or e_7 for $e > 0$ and as e_5 for $e < 0$. The transition must be defined separately for that. Another possibility is to find a fitting control error for a situation along a Pareto front consisting of multiple possible control errors. Alternatively, solely positive or negative control errors like e_0 or e_9, whose minimum deviation from $e = 0$ seems to yield a desirable trade-off between detection quality and energy consumption, could be used or eventually adapted. First results of using these control errors in the closed control loop with a PID controller with successive empirically determined control parameters show that this assumption can be correct. However, e never becomes zero but stays stable at the same value. Other control errors, like e_5 also basically work for the closed loop, achieving an $e = 0$. However, there might be other control errors than those in this contribution that could be more fitting. As mentioned in Section 3, one possibility for a dynamic control loop can also be a sampling-based optimization to determine the change direction for each material intensity, according to whether decreasing or increasing the luminous intensity is beneficial.

5 Conclusion & Outlook

The contribution at hand presented a novel concept for controlling matrix headlights with a control loop to achieve a compromise between detection quality for computer vision in automated driving and energy consumption using material properties of the environment. One focus was the definition of the control error, which is dependent on the determination of the reference value and the measured output of the sensor and data processing system. Multiple possibilities for the control error and thus the measured output were discussed, where every control error yields advantages and disadvantages. However, even if none of the presented control errors can be both positive and negative in value while correctly representing especially the detection quality in every situation, first results in a closed control loop show that with most of them, it is possible to find a trade-off between detection quality and energy consumption. Whether this is really the desired trade-off is the focus of another contribution. Future work also includes further investigations regarding the definition of the control error, e.g., by combining multiple control errors for certain situations along a Pareto front of control errors. Moreover, The PID controller of the control loop must be designed and analyzed in the closed control loop, especially considering the individual PID parameters for each material intensity.

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