Stray light analysis of high-dynamic-range cameras based on digital image processing

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In video based driver assistance systems, cameras with high-dynamic range CMOS sensors are highly susceptible to glaring illumination and thus, stray light artefacts might occur. In this paper we present an approach for an automated stray light analysis based on digital image processing and supervised statistical learning. Cross-validation results show an artefact detection rate of about 93 %

1 Introduction

Video based driver assistance systems are gaining increased importance in the domain of night vision improvement or object and lane measurements. The active infrared night vision system of Bosch (see Fig. 1 left) provides a three times more extended visibility at night compared to conventional low-beam headlights without blinding oncoming traffic. The road scene illuminated by infrared light is recorded by a high-dynamic-range CMOS (HDR) camera (Fig. 1 right) and presented as a black-and-white image on a display. The HDR camera is able to capture the outperforming wide luminance range of night sceneries using a nonlinear conversion (for a more detailed description see [1]).

Fig. 1 *Night Vision system of Bosch (left) and HDR camera (right)*

During serial production, these cameras are tested for various optical parameters such as focus, contrast, resolution and sensitivity to stray light. Thereby, the performance of HDR cameras is especially critical if being exposed to glaring situations in typical street sceneries with uncontrollable illumination, for example by oncoming traffic or reflection at traffic signs. Due to mechanical defects or contamination of the imager or lens, different stray light artefacts might be amplified by the HDR CMOS sensor and occur as beams and fans of varying lengths or different halo sizes as well as sidelight structures in the images (Fig. 2). So far, cameras were tested by visual inspection by means of a failure catalogue. In order to ensure the reproducibility and repeatability of test results, enhance the test coverage and at the same time reduce test duration, an objective and automated stray light analysis was developed. While moving the camera under test by means of a motor unit in dark surroundings, images are acquired which show an external light source mapped as bright spot on dark background at different positions. In the following, a machine learning algorithm will be presented which provides reliable results in detecting stray light artefacts.

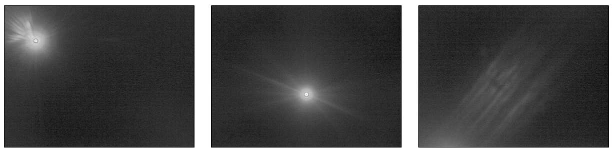

Fig. 2 *Various stray light artefacts; left: fan, middle: beam, right: side light*

2 Algorithm for objective stray light analysis

The aim of the introduced machine learning algorithm is the classification of the cameras into a defect or non-defect class by evaluating statistical features of image intensities. As stray light artefacts are, however, characterized by blurred intensity differences and show a large range in appearance, an approach based on supervised statistical learning in combination with image processing is applied as opposed to a simple analysis of intensity measures. The classification can be subdivided into two steps: (a) training of the classifier and (b) actual prediction of the class in each image by application of the classifier. First of all, training data with different artefacts as well as images without artefacts are collected. By means of visual inspection, every image gets the label *n.i.O.* if it contains an artefact and *i.O.* if it does not. After image pre-processing like noise reduction for example, the next step is to extract generic statistical features from the intensity pattern such as maximum, mean, standard deviation and more [2]. These features are merged to a row vector for each camera under test.

The composition of all row vectors together with their labels result in a matrix which provides the input for the training of the statistical learning model. After being trained, this model can be used for the detection of artefacts in test images not seen during the training on basis of the same feature extraction.

The performance of the model is evaluated by a *k*-fold cross-validation (CV) procedure which subsequently splits up the training dataset with a-prior known labels into *k* blocks. Each run of the CV, *k-1* blocks are used for the training of the model. Afterwards, the class of each image in the left out block is predicted by the trained model. These steps are repeated *k* times. The comparison between the predicted and a-prior known class labels provides the prediction accuracy of the model on different but overlapping training sets. Apart from the predicted artefact probability in each image (see Fig. 3 left), the results of the CV are presented by a receiver operating characteristic (ROC) analysis (see Fig. 3 right). For this purpose, a threshold is incrementally increased from 0 to 100 %. All images with an artefact probability above that threshold are assumed to contain an artefact, while all other images are assumed to be non-defect. The ROC curve shows the true-positive rate (tpr) over the false-positive rate (fpr) with respect to each threshold, i.e. the probabilty that an existing artefact is actually detected over the probabilty that an artefact is acidentally predicted. A summarizing measure is the area under the ROC curve (AUC) in percent (see Fig. 4). Thus, an optimal ROC curve with an AUC of 100 % has a tpr of 100 % while the fpr is zero. This means that an appropriate threshold exists which leads to a good classification result. For more details in statistical learning methods and the evaluation please refer to [3].

3 Discussion of results

To assess the performance of the proposed stray light analysis, we have acquired images with fans, sidelight and beams as well as images without any artefacts, extracted the features and deployed a cross-validation with $k = 5$.

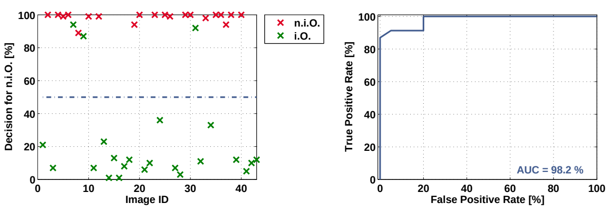

Fig. 3 *Results of stray light analysis on the example of side light; left: predicted artefact probability of each image in test data; right: ROC curve*

As an example, Fig. 3 depicts the prediction results and ROC curve of one CV run for the sidelight artefact. For each image on the x-axis, its position on the y-axis shows the predicted probabilty containing an artefact. An image with a red cross actually contains an artefact, green means that it does not. Suppose we take a threshold of 50 %, all images with an artefact are classified properly, while three images not containing any artefact have a predicted artefact probabilty of more than 50 % and thus, will be misleadingly assumed to contain an artefact. Fig. 3 shows the corresponding ROC curve which leads to an area under curve of 98.2 %.

A comparison of AUC values of each CV run between fans, sidelight and beams is depicted in Fig. 4. In the case of fan artefacts, only one CV run leads to an AUC slightly lower than 90 %, while all other CV runs have higher AUC measures, even up to 100 %.

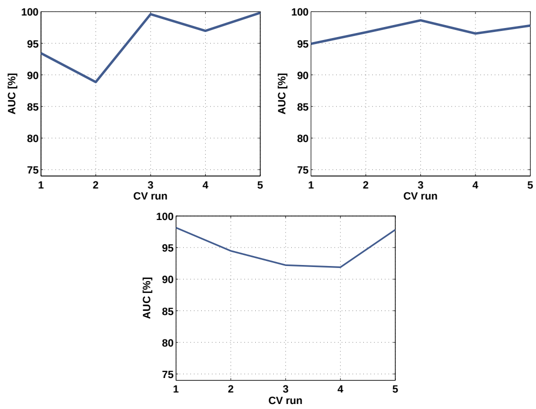

Fig. 4 *AUC results from cross-validation; top left: fan, top right: beam, bottom: side light*

4 Conclusion and outlook

The results of the stray light analysis conceal an average AUC value of about 93 % for different artefact types. In conclusion, this paper presents an approach of statistical learning based on digital image processing for automatic detection of stray light artefacts of high-dynamic range cameras.

The extraction of more robust features as well as an accompanying sensitivity analysis is expected to improve results in future. Additionally, images with a vague artefact probability will be analysed. Finally, the approach will be optimized for the application in test engineering during the production process.

References

[1] B. Hoefflinger, *High-Dynamic-Range (HDR) Vision: Microelectronics, Image Processing, Computer Graphics* (Springer, 2007).

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[3] C. M. Bishop, *Pattern Recognition and Machine Learning (Information Science and Statistics*, 2nd ed. (Springer, 2007).