Towards Video Processing in Vehicles under Adverse Weather Conditions

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ABSTRACT

In this contribution we propose methods for vehicle detection and tracking for the Advanced Driver Assistance Systems (ADAS) that work under extremely adverse weather conditions. Most of the state-of-the-art vehicle detection and tracking methods are based either on appearance based vehicle recognition or on extraction and tracking of dedicated image key points. Visibility deterioration due to rain drops and water streaks on the windshield, swirling spray, and fog lead to a drastic performance reduction or even to a complete failure of these approaches. In this contribution we propose several methods for coping with these phenomena. In addition to an extension of the feature-based tracking method, which copes with outliers and temporarily disappearing key points, we present a detection and tracking method based on search for vehicle rear lights and whole rear views in the saturation channel. Utilization of symmetry operators and search space restriction allows to detect and track vehicles even in pouring rain conditions. Furthermore, we present two applications of the above-described methods. Estimation of the strength of spray produced by preceding vehicles allows to draw conclusions about the overall visibility conditions and to adjust the intensity of one's own rear lights. Besides, a restoration of deteriorated image regions becomes possible.

Keywords: ADAS, adverse weather conditions, rain, spray detection, tracking, image restoration, ICADAC

1. INTRODUCTION

Camera-based advanced driver assistance systems (ADAS) have become available in many new series vehicles. With increasing acceptance of such systems there comes an increasing expectation of their performance. In the last decades a lot of research has been done in the field of video-based object detection and tracking for intelligent vehicles.[1] A topic that has been often neglected is the influence of the weather conditions on the data quality and thus on the system performance.[2] Rain drops and water streaks on the windshield may cause strong distortions as shown in Figure 1 (a). This and further effects of rainy weather disturb image processing algorithms and result in poor system performance when used under adverse weather conditions, especially in pouring rain.

There exist several image processing algorithms for locating drops on the windshield in a single image. This information is then utilized in order to exclude the locally degenerated image parts from further processing or even to revert the induced distortions.[3–5] However, a detection of single raindrops on the windshield requires a camera installation that is not common to most video based driver assistance systems. Most of the currently used camera installations have a small distance to the windshield, so that the windshield and the rain drops are out of focus. The identification of single rain drops becomes impossible. Especially in heavy rain conditions a single rain drop may affect large image regions rather than a single spot as shown in Figure 1 (a) and (b). Moreover, with increasing speed and rain intensity a proper visibility of the relevant objects is given only within a few frames captured right after the passing of the windshield wiper. Further disturbing effects are obfuscation due to spray and occlusion through the windshield wiper as shown in Figure 1 (c) and (d). With those effects it is nearly impossible for conventional image processing algorithms to achieve the desired quality or even to ensure a correct functionality. The challenge is to detect the occurred defects and to adapt further image processing accordingly.

This paper describes a way to detect and track vehicles under extreme adverse conditions against the backdrop of a spray estimation. Information about the amount of spray produced by the preceding vehicles could be used

(a) Rain drops and water streaks on the windshield induce strong distortions.

(b) Single rain drops on the windshield are not identifiable, they affect large image areas.

(c) The preceding vehicle in the left lane is barely seen due to swirling spray.

(d) Occlusion of relevant image regions through the windshield wiper.

Figure 1. Examples of image defects at rainy weather.

for estimation of the visibility of the one's own illumination (rear lights, break lights) and for controlling its brightness according to the current visibility.

The remainder of this paper is divided into five parts. In Section 2 an enhancement of the feature based object tracking[6,7] is presented. It can handle outliers induced by wrong correspondences and distortions that are induced by rain drops and water streaks, temporary disappearance of feature points due to the blurring effects of spray and raindrops, and occlusions induced by the windshield wiper. An alternative vehicle detection and tracking approach designed for extreme adverse weather conditions is presented in Section 3. It is based on the analysis of gradients in the saturation channel and other features such as symmetry. In Section 4 two approaches are described which allow to detect spray raised by preceding vehicles and estimate its amount. One of those approaches is based on the intensity histogram evaluation while the other approach classifies the image of the tracked vehicle using a support vector machine. Section 5 deals with image restoration. Finally, a short summary and an outlook is given in Section 6.

2. ADAPTATION OF THE FEATURE-BASED OBJECT TRACKING TO RAINY VIDEO SEQUENCES

Tracking of objects in video sequences is often done by tracking local feature points.[6–8] The displacement of the corresponding feature points in consecutive images allows to estimate e.g. a shift and a scaling of the object image. Exploitation of either geometric constraints or depth information provided by e.g. a stereo camera allows to additionally estimate a 3D motion.

Heavy rain introduces some phenomena that may severely disturb this approach. Rain drops and water streaks induce distortions which cause feature points to appear far from the expected position. An example of such distortions can be clearly seen on Figure 1 (a). An integration of the measured displacement of such distorted feature points (outliers) may heavily disturb the whole tracking process. Further phenomena are given by blurring effects through rain drops, water streaks, and spray as well as by temporary occlusions through spray

clouds and windshield wiper passages. Image feature points from the previous image can not be redetected and get lost as it can be seen in Figure 2.

In order to ensure a reliable tracking under such adverse conditions, all feature points are saved into a buffer. If a feature point can not be found in the consecutive image, further subsequent images are considered. Feature points which could not be detected in the consecutive image because of errors can often be redetected in the following images as shown in Figure 2. For robust estimation of the model parameters despite outliers we use a modified version of the RANSAC algorithm. The best consensus set is chosen not as the set having maximal number of inlier points, but depending on the weighted sum of these. The weighting takes into account both the error value e and a quality measure regarding repeated point re-identification. The total weight w of an inlier is calculated as the product of the model error weight $w_m = (e_{max} - e)/e_{max}$ and the tracking quality weight $w_t = m/t$ with e_{max} being the error threshold, i.e. the error value from which on a point is considered an outlier. The tracking quality weight w_t is computed as the ratio of the number m of successfully matched frames (i.e. frames, in which the point has been successfully re-identified) to the total object tracking duration t (measured in frames).

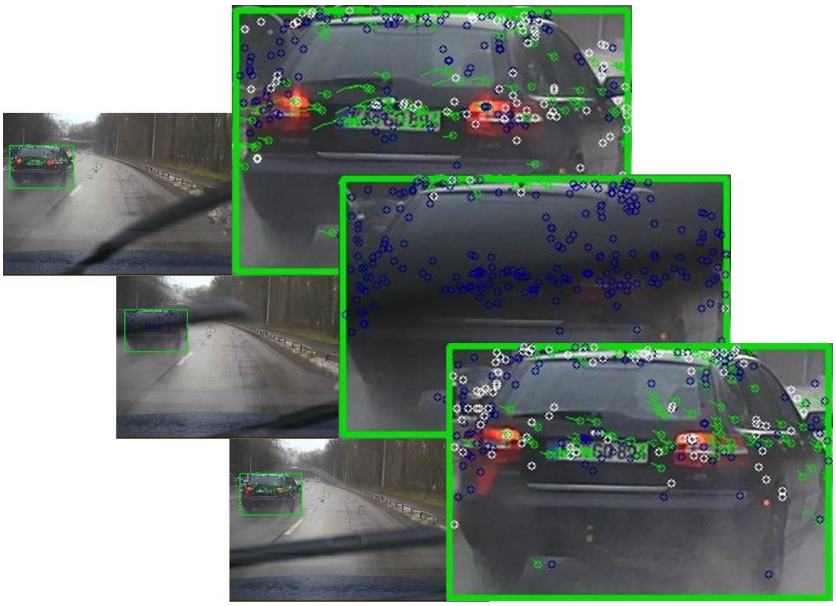


Figure 2. Object tracking using local features.
White points: new feature points, green points: feature points tracked from one of the previous frames, blue points: points which could not be re-detected. Green lines visualize motion of the tracked points.

The application of the described adaptations helps to overcome temporary image corruptions and to achieve a noticeable stabilization of the feature-based tracking.

3. DETECTION AND TRACKING UNDER ADVERSE CONDITIONS

Adverse visibility conditions due to rain drops and water streaks on the windshield, swirling spray, and fog make most of the common vehicle detection and tracking methods that are based on feature extraction or appearance based vehicle recognition fail. In order to provide an alternative detection and tracking strategy for adverse weather conditions we propose a method based on the analysis of the saturation channel. Hereby we utilize information from extrinsic camera calibration in order to determine a search corridor for vehicle detection. In order to detect vehicle candidates a search window is moved along the search corridor. Maxima search and edge extraction in the saturation channel with consecutive dilatation allow to generate eroded binary images. The resulting blobs correspond mostly to the rear lights or whole vehicle rears as shown in Figure 3. With those features it is possible to search for vehicles whose width is within a predefined tolerance range. If a pair of rear lights or a vehicle rear meet those requirements, a symmetry operator evaluates the object candidates. The

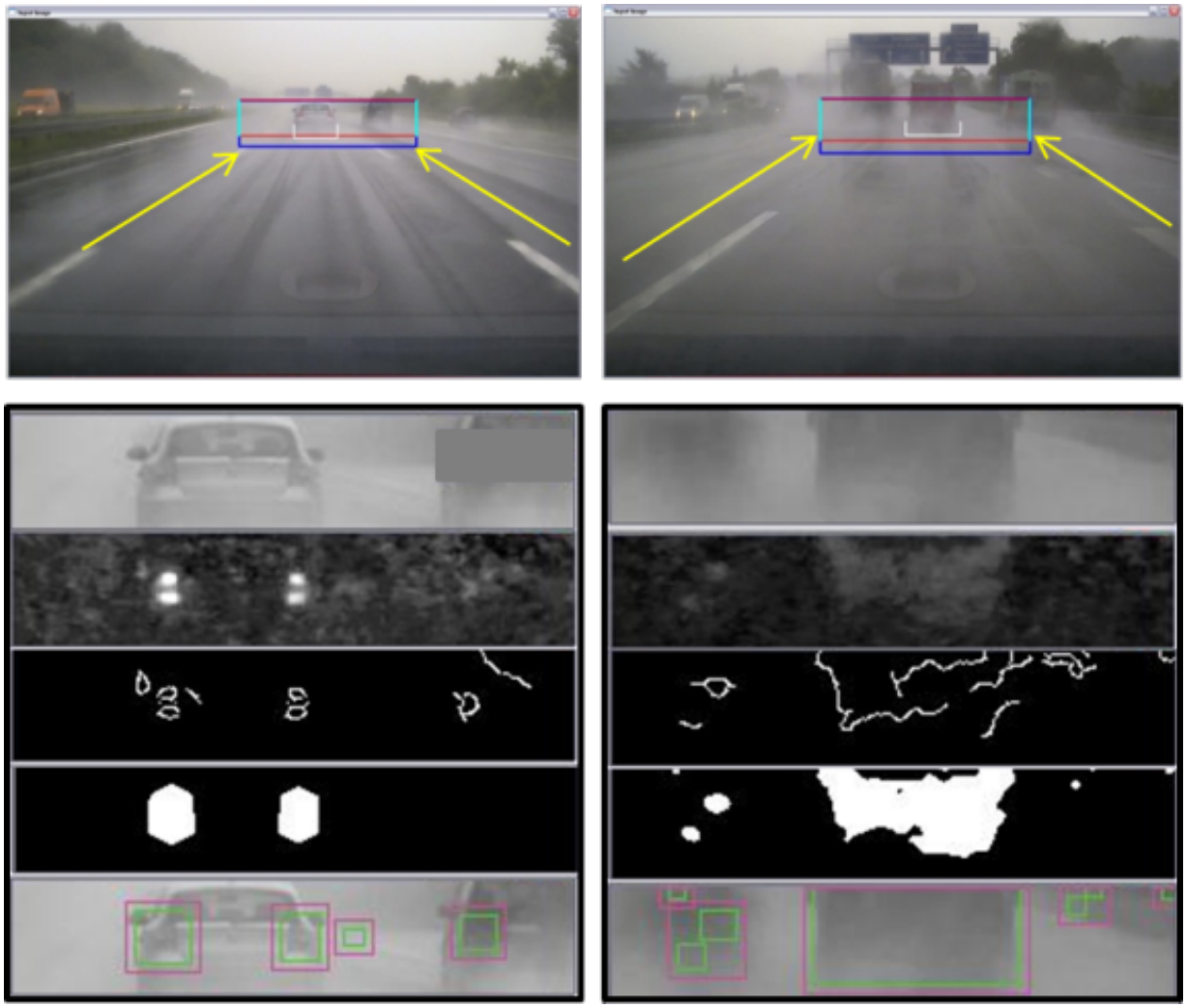


Figure 3. Vehicle detections under adverse conditions.
From top: 1. Restriction of the search area by exploiting calibration information.
2. Intensity image. 3. Saturation channel. 4. Edge image of the saturation channel.
5. Eroded binary saturation channel. 6. Detected hypotheses.

evaluation is done in the original intensity image, in the smoothed saturation channel as well as in the edge image. The normalized correlation coefficient serves as a measure for the symmetry. If the mean of correlation values exceeds a predefined threshold a vehicle detection is reported.

The tracking is realized as a search in a reduced search space around the previous detection. We perform a cross-correlation with a reference vehicle image from the last frame. The new vehicle position in the image is updated using image coordinates at which the highest correlation has been achieved. This approach proved to be useful for refining the localization.

Another refinement approach is based on the analysis of the intensity histograms of the individual image lines within the search window. If the intensity occurrences are plotted as a height over the corresponding values as the abscissae and the line numbers as the ordinates as shown in Figure 4 (b), one can clearly identify a vertical ridge. The transition between the vehicle and the pavement manifests itself as a bend in this ridge. Detection of this bend allows to further refine the vertical position of the vehicle in the image.

If a vehicle can not be re-detected for a long time, the detection process and the search corridor are re-initialized.

(a) Original images with regions of interest (ROIs)

(b) Content of the ROIs

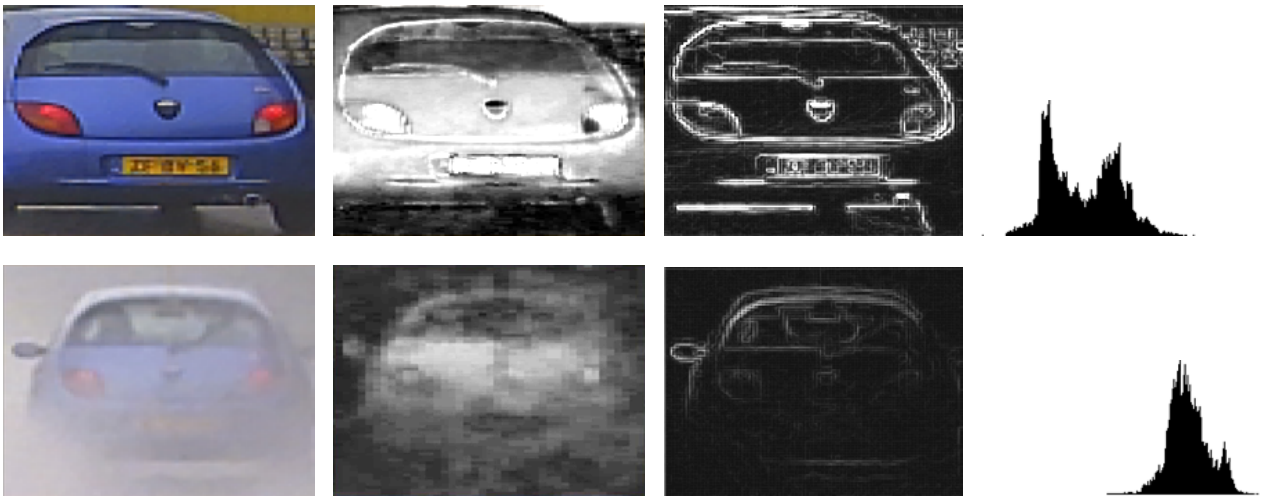
(c) Linewise intensity histograms of the ROIs. Each line contains intensity histogram of the corresponding ROI line. Abscissae encompass intensity values from 0 to 255.

Figure 4. Exploitation of the intensity histogram. Top: scene with no spray, bottom: scene with strong spray.

4. SPRAY DETECTION AND CLASSIFICATION

A possible application of the previously described detection and tracking methods is the spray detection. By detecting spray of a preceding vehicle and by estimating its intensity, it is possible to estimate deterioration of the visibility of the own vehicle by spray. Besides, a restoration of the deteriorated image regions for usage in further ADAS algorithms is possible.

At first we examined the effects of spray in images. Images taken in dry and wet scenes have been compared according to various characteristics. The comparison shows that areas with spray appear mostly gray-white and have characteristic intensity values and a low saturation. In addition, both the intensity variance as a global feature and the gradient as a local feature for edges are lower in regions with spray than in regions without spray (s. Figure 5).



(a) Original images

(b) Saturation channel

(c) Edge detection

(d) Intensity histograms

Figure 5. Effects of spay in the images. Top: Vehicle on a dry road. Bottom: vehicle on a wet road.

As a result we propose two approaches for spray detection. The first one is based on the analysis of linewise intensity image histograms of the border regions between vehicles and pavement. As shown in Figure 4 the width of the histogram tube and the jerkiness on the border between the vehicle and the pavement deliver indices for spray intensity. If there is much spray, the variance of the intensity histogram is substantially lower and a transition from car to pavement is hardly noticeable. In contrast, when the pavement is dry there is a larger variance and one may clearly see a jump in the histogram ridge at the transition from road to vehicle. Hence, consideration of the maxima of the linewise intensity histograms and the sum of the variances allows to measure the intensity of the spray.

The second approach is based on the analysis of the rear views of preceding vehicles. Since it is hardly possible to derive an analytical distinction between scenes with spray and dry scenes, the classification is done using a Support Vector Machine (SVM). The rear view of a detected vehicle is divided into rectangular cells. For each cell we compute values that are characteristic for spray. Those values are the average intensity value, the intensity variance, the mean color saturation, and the mean gradient - a value that indicates the presence and the strength of edges. In order to derive an overall spray intensity measure, the characteristic values of the individual cells of a vehicle rear view are gathered into a vector. This allows to account for local differences in the appearance of the spray.

The SVM has been trained based on the manually labeled vehicle rear views. When training the SVM and performing the classification, only two classes ("spray" and "no spray") were used. However, the distance d to the separation hyperplane of the SVM was used as the measure for the spray intensity. In order to perform an evaluation we defined four categories of vehicle rear views regarding to the spray content: "no spray", "light spray", "medium spray", and "heavy spray". All images in the test data set were labeled according to these categories (although such manual labeling yields a rather subjective classification). Figure 6 shows the distributions of the SVM output for the four categories. As one can see, a good separation (at least regarding the both classes "no or little spray" and "heavy spray") seems reasonable. The results of the evaluation are summarized in Table 1. In order to automatically classify the spray amount following thresholds have been used: $d < -1$: "no spray", $-1 < d < 0$: "light spray", $0 < d < 1$: "medium spray", $d > 1$: "heavy spray".

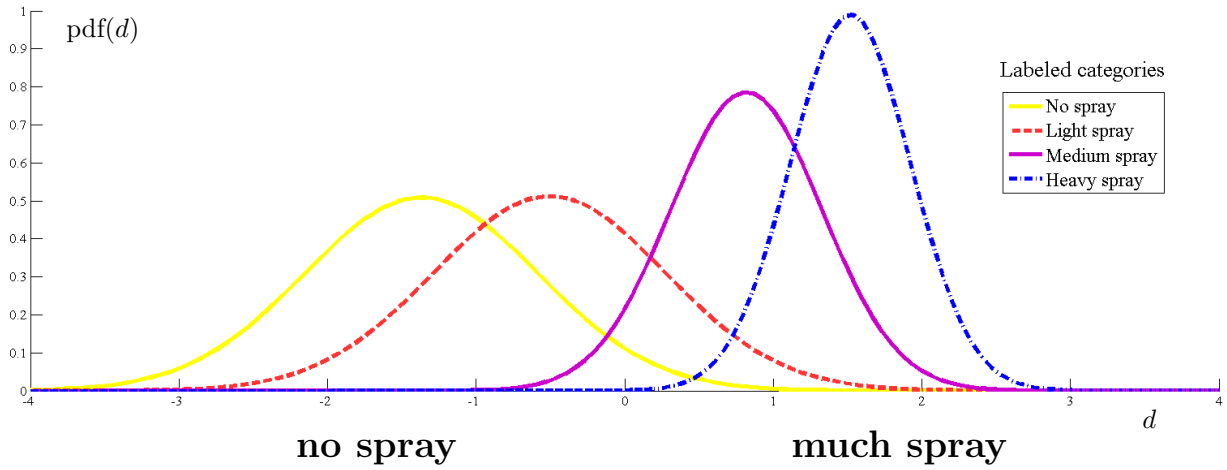
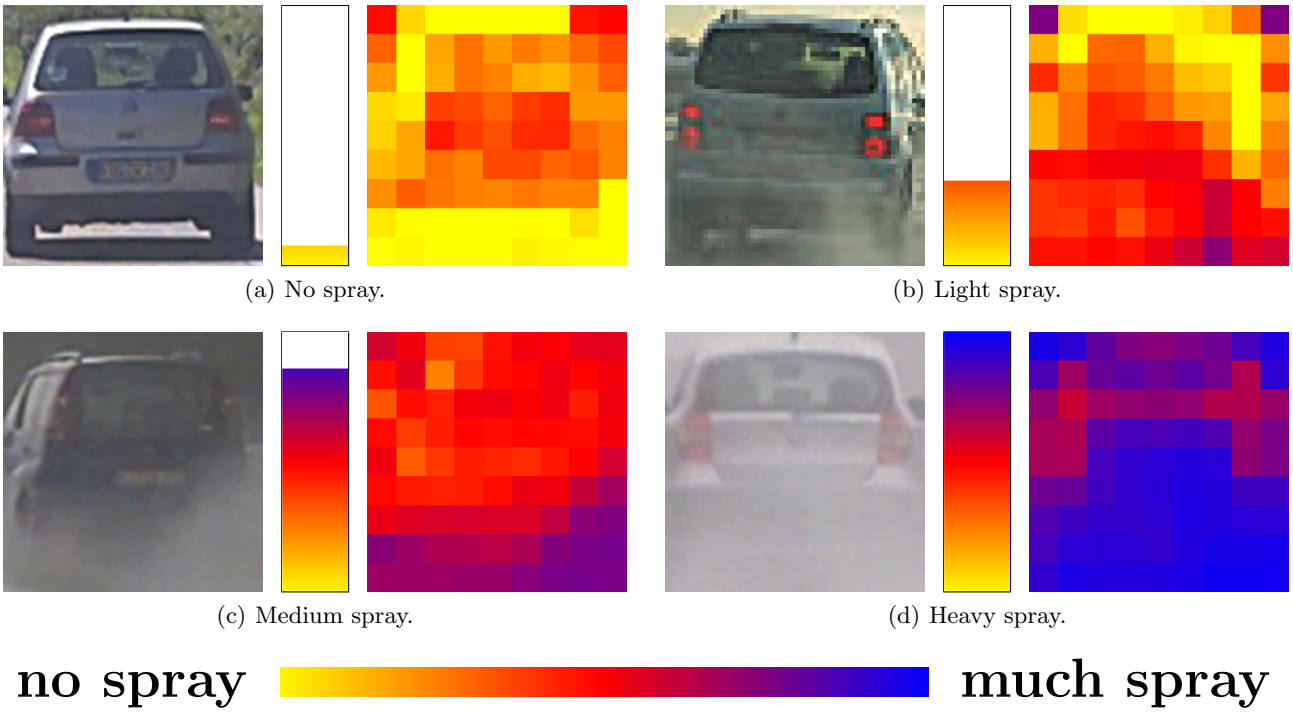


Figure 6. Probability distribution of the classification output for the four pre-labeled image classes.

classified as / class	no spray	light spray	medium spray	heavy spray
no spray	67.7 %	28.6 %	3.5 %	0 %
light spray	28.2 %	41.7 %	29.1 %	1.0 %
medium spray	0 %	1.3 %	57.9 %	40.8 %
heavy spray	0 %	0 %	11.3 %	88.7 %

Table 1. Confusion table of the categorization results when using manually set thresholds.

An exemplary graphical representation of the classification results is given in Figure 7. Additionally to the classification of the entire rear views which is shown in the second column of the subfigures we have tested a classification of the individual grid cells. Results of this classification are shown in the third column. Together with the overall spray intensity value this information may be used for estimating the visibility of the rear lights and adapting their intensity. Besides, this information can be exploited in order to perform restoration of the deteriorated image regions as it will be shown in the next section.



(a) No spray. (b) Light spray.

(c) Medium spray. (d) Heavy spray.

Figure 7. Results of the SVM based spray intensity classification. Second column: overal spray intensity value. Third column: spray intensity estimation of the individual cells.

5. IMAGE RESTORATION

Vision-based driver assistance systems mostly rely on objects being visible for multiple consecutive frames. In adverse weather conditions however, the visual appearance of vehicles varies heavily over time. Especially dynamic spray effects and the windshield wiper passages lead to visual appearances of different quality. Using both the tracking of objects and the local spray estimation described in the above sections, an image restoration approach is possible which combines the object's visual information of different temporal frames.

In order to improve the image of an object in the current frame we therefore locally replace the deteriorated patches of the object by better patches from the history. The history of the visual appearance of an object images is available from the tracking. In order to assess the quality of local image regions of an object we use both the local spray estimation and the contrast in the local cell. If the cell is identified as being deteriorated (i.e. if the estimated spray intensity is too high or no features could be extracted), the content of the cell is replaced by the content of that cell from a frame where this cell had the lowest spray value and contained most contrast. In order to fit the old content into the current cell, it is resized depending on the current cell size. After the restoration object images sometimes have sharp edges at the cell borders. This resampling effect might lead to difficulties for post-processing algorithms and should hence be reduced. In order to achieve this we locally smooth the affected regions at the cell borders preserving the edges detected in the respective original cells.

Figure 8 shows the result of the restoration. Although in the original image the object is almost completely hidden behind the windshield wiper the vehicle could be restored using local visual information from the previous frames.

(a) Original image (b) Restored image (c) Close-up of the restoration region

Figure 8. Restoration of the vehicle appearance in deteriorated regions using patches from previous frames.

6. CONCLUSION AND OUTLOOK

In this paper we presented several video processing methods that can be used in ADAS for coping with the effects of adverse weather conditions. The first one is an enhancement to feature-based tracking which copes with outliers and temporarily disappearing feature points. Further we proposed a method for detecting and tracking vehicles under heavy rain by analyzing the saturation channel and by additionally exploiting calibration information, symmetry constraints and properties of the linewise intensity histograms. The analysis of the vehicle rear views allows to detect spray raised by the preceding vehicles and to estimate its intensity. This information is used as an input for an advanced driver assistance system which controls the brightness of the backlights in order to adapt it to the current visibility conditions. Finally, a restoration of deteriorated image regions based on the analysis of the current detection and results of vehicle tracking has been presented.

Both detection and tracking of vehicle rears and subsequent spray detection and image restoration have been tested only for scenes captured during daylight and the performance during night remains to be explored.

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