Road Condition Estimation based on Spatio-Temporal Reflection Models

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Abstract. Automated road condition estimation is a crucial basis for Advanced Driver Assistance Systems (ADAS) and even more for highly and fully automated driving functions in future. In order to improve vehicle safety relevant vehicle dynamics parameters, *e.g. last-point-to-brake* (LPB), *last-point-to-steer* (LPS), or *vehicle curve speed* should be adapted depending on the current weather-related road surface conditions. As vision-based systems are already integrated in many of today's vehicles they constitute a beneficial resource for such a task. As a first contribution, we present a novel approach for reflection modeling which is a reliable and robust indicator for wet road surface conditions. We then extend our method by texture description features since local structures enable for the distinction of snow-covered and bare road surfaces. Based on a large real-life dataset we evaluate the performance of our approach and achieve results which clearly outperform other established vision-based methods while ensuring real-time capability.

1 Introduction

The continuous improvement of road safety is an important field of research and development in the automotive industry. Considerable efforts have been made to reduce the number of road fatalities, damages and the consequences of accidents, *e.g.* by automated emergency brake systems [10], road detection for lane departure warning [2], or vulnerability prediction [18]. Advanced Driver Assistance Systems (ADAS) which warn and support the driver in normal driving and especially in hazard situations form an important contribution towards "vision zero" [6]. As for example to assess a critical driving situation properly the understanding of the present road condition is of vital importance. Nowadays, this information is determined manually by the driver but is intended to be estimated automatically to serve as input for higher automated vehicle safety systems. Based on this valuable information the effectiveness of current assistance systems can be increased considerably, *e.g.* by adapting system thresholds such as *last-point-to-brake* (LPB) for automated emergency brake systems. Furthermore, it is desired to obtain the current road condition automatically for the purpose of highly and fully automated driving in the future.

Recent advances in road condition estimation based on on-board surrounding sensors, as for example rain, humidity, or laser sensors, have proven to be the key element for the task at hand. Another potential resource are visual sensors which have the advantage of being already integrated in many of today's vehicles. Additionally, cameras allow for hazard prediction as they asses the area directly in front of the moving vehicle. Thereby, the most difficult task is the recognition of wet and icy areas, being some of the most dangerous situations. By using stereo vision systems this challenge can be addressed by utilizing polarization filters [7] to obtain information about the presence of reflections as a typical indicator for those conditions. However, since the market penetration of stereo camera systems is very low compared to mono camera systems, road condition estimation has to be performed on monocular image data which renders the task very challenging.

In this paper, our goal is to overcome limitations of road condition estimation based on single cameras in order to distinguish between dry, wet and snow-covered road surface conditions. In particular, we apply enhanced spatio-temporal reflection models combined with strong texture description features. Furthermore, our proposed method is very robust to occurring disturbances and achieves real-time capability.

In Sect. 2 we give an overview of related work and motivate our approach. Sect. 3 presents our novel method in detail based on previously introduced standard techniques for reflection modeling. In Sect. 4 the actual road condition estimation framework is explained which is currently implemented in a first demonstration vehicle. A comprehensive evaluation on a large real-life dataset is finally presented in Sect. 5.

2 Related Work

In the past decades several approaches have been developed for the challenging task of road condition estimation. There are mainly two approaches to provide weather-related information for individual vehicles. On the first hand, so-called road side units [16] collect data in a specific region by a variety of sensors. Afterwards, these statistics are processed and distributed to individual vehicles as presented in [13]. On the other hand, this network can be supported by each particular vehicle as well by utilizing on-board surrounding sensors for rain [8], air humidity [21], acoustics [1, 12], and surface roughness [5].

In the area of pure computer vision, the most challenging task is to detect wet road surface conditions. Usually, this problem can be addressed by using a stereo camera setup utilized with polarization filters [7]. To be able to distinguish between dry, wet and snowy conditions, polarization characteristics are combined with additional image feature types like *gray level co-occurrence matrices* [17, 24] or *wavelet packet transforms* [25].

However, in the absence of a stereo camera system, as it is commonly the case for most of the today's vehicles, more elaborate features based on single cameras have to be developed. As for example in [19, 20] sole texture description followed by a dimensionality reduction technique is applied for stationary road condition estimation. Examples for on-board systems are presented in [9, 22] where texture characterization based on *gray level co-occurrence matrices* is the key element. In the work of [9] texture description is extended by additional block-wise RGB ratios to obtain color and luminance features. Another interesting method presented in [15] applies block-wise RGB histograms combined with edge histograms considering the entire lower image region in order to cover additional information.

In the case of monocular image analysis it is still difficult to detect wet areas due to the high variability of the appearance of those regions caused by mirrored environmental objects. To overcome these difficulties certain road conditions can be determined by modeling different reflection types based on spatio-temporal information, *i.e.* taking an image sequence into account. In the course of this, typical reflections for wet situations, namely *specular reflections*, are modeled by investigating appearance variations of individual road surface regions as presented in [23]. The major drawback of this approach is the required time-consuming registration of individual regions which is also prone to unregistered movements of the vehicle.

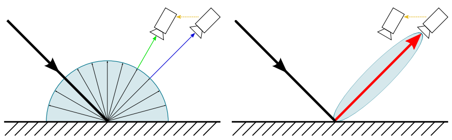
Therefore, in this work we present a novel approach to model reflection types by not considering individual regions directly but by evaluating the paths those regions pass. By assuming an almost linear motion of the vehicle together with an appropriate image transformation, considered regions will pass the scene through individual image columns which then provide all relevant information of potential appearance changes. This enables us to avoid expensive and unstable registration techniques in contrast to other works. We then combine our novel reflection features with strong texture description to obtain a robust and fast approach for the challenging task of road condition estimation.

3 Fast and Robust Reflection Modeling

The most difficult part of road condition estimation is the recognition of wet areas on the road surface. Due to the high variability of the appearance of wet regions particularly caused by unpredictable mirrored environmental objects, features such as texture description, color information, statistical moments, etc. turned out to be not very discriminative. However, exactly those mirrored objects are considered as key elements for wet surface recognition in our paper. The main issue is to not only consider one single frame but to evaluate a sequence of consecutive images. With the help of this spatio-temporal modeling the nature of different reflection types can be revealed. This allows for the recognition of wet surfaces in a very general way. Thus, in the following sections different reflection types together with their properties are introduced in detail. Afterwards, a basic approach for the detection of a specific reflection type indicating wet conditions–namely *specular reflections*–is presented. Motivated by serious shortcomings of this basic technique a novel method for the recognition of reflection types is introduced in Subsect. 3.3.

3.1 Diffuse and Specular Reflections

As mentioned above our main assumption is that identifying surface reflection types allows for the distinction between the underlying road condition. In Fig. 1 (a) and (b) the difference between diffuse and specular reflections is depicted. In the case of dry asphalt as well as snow coverage fine-grained structures on the surface reflect incident light in all directions equally. Thus, a change of the perspective would lead to the same visual appearance of the focused region. In contrast, a surface covered by water is very smooth which has the properties of a mirror and thus the incident light is theoretically



(a) diffuse reflection (b) specular reflection

Fig. 1. Scheme of different reflection types. In (a) diffuse reflection is shown where the incident light is equally scattered in all directions. A change of the viewpoint has no visual effect on the observed surface point. In (b) a specular reflection is depicted and the reflected light is focused into one single direction. An altered perspective would lead to an appearance shift of the observed surface, since the particular reflected ray would no longer meet the camera.

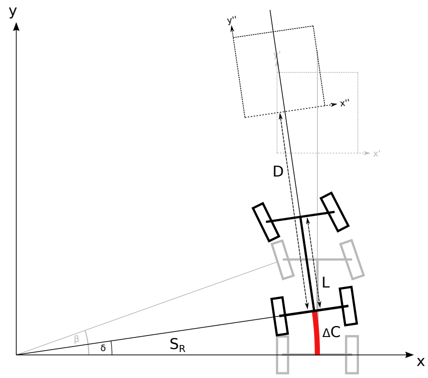


Fig. 2. Schematic representation of recovering individual regions on the road in consecutive frames based on the one-track-model.

reflected in exactly one direction. If the perspective changes, this reflection will no longer encounter the observer's view and the region seems to change its appearance.

To decide about the presence of specular reflections and thus the occurrence of wet road conditions, potential appearance changes of individual regions have to be evaluated. This can be realized by comparing identical regions on the road between several consecutive frames. In the following section a basic method is presented which allows for the examination of particular regions with respect to the presence of specular reflections given a sequence of images.

3.2 Physical Model

To decide about the present reflection type it is required to evaluate the change of appearance of individual regions on the surface along consecutive frames. Therefore, corresponding pixel values of those regions have to be considered. To be able to align such regions over different frames it is beneficial to project the original image into a top view image based on an estimated homography. Hence, potential transformations are reduced to simple translation and rotation. To obtain the geometric transition between two consecutive frames *vehicle dynamics parameters* have to be taken into account. Those parameters–available from the vehicle's system–provide the current steering angle as well as the actual velocity and thus the distance traveled during two acquired images. In Fig. 2 the geometric relationship between two frames is shown exemplarily. As can be seen an individual point (x', y') placed in the top view image of frame f' can be recovered as (x'', y'') in the subsequent frame f''. The corresponding transformation between these points can be expressed in general by

$$
\begin{aligned}
x'' &= (x' + S_R) \cdot \cos\left(\frac{\Delta C}{S_R}\right) + (y' + D) \cdot \sin\left(\frac{\Delta C}{S_R}\right) - S_R \\
y'' &= -(x' + S_R) \cdot \sin\left(\frac{\Delta C}{S_R}\right) + (y' + D) \cdot \cos\left(\frac{\Delta C}{S_R}\right) - D,
\end{aligned}
\tag{1}
$$

where S_R is the pole distance, ΔC is the distance traveled, and D is the offset between rear axle and the region of interest. Additionally, the pole distance can be obtained by $S_R = \frac{L}{\tan(\beta)}$ where L denotes the distance between rear and front axle. However, β increases proportionally with the current steering angle for which the relationship has to be estimated in advance. As can be seen $\delta = \frac{\Delta C}{S_R}$ is basically the angle of the rotation matrix for the required image transformation.

Once all frames are registered and related regions are aligned the evaluation of potential appearance changes can be applied. The most intuitive way is to determine the gray value variances of corresponding pixels along the time axis which can be enhanced by considering grid cells instead of single pixels to avoid misalignments caused by small transformation errors. The result of this procedure is an image containing the variance over time at each pixel location and thus an indication of the present reflection type. However, under real world conditions, serious problems arise due to the technical setup as well as the simple assumptions. At first, erroneous transformations between two frames can be obtained due to the fixed homography in combination with common vertical movements of the car. Those errors increase drastically for regions which are far away from the observer. In order to rectify the biased transformation it is possible to adapt the homography for each frame individually based on ground-plane estimation. However, the estimation over several frames leads to cumulative errors in terms of subpixel accuracy caused by the coarse discrete scale of the *vehicle dynamics parameters*, *e.g.* the steering angle. To resolve these problems, in the following, we propose a novel fast and robust reflection modeling approach which can easily deal with inaccurate motion estimation.

3.3 A Novel Approach: Specular Reflection Maps

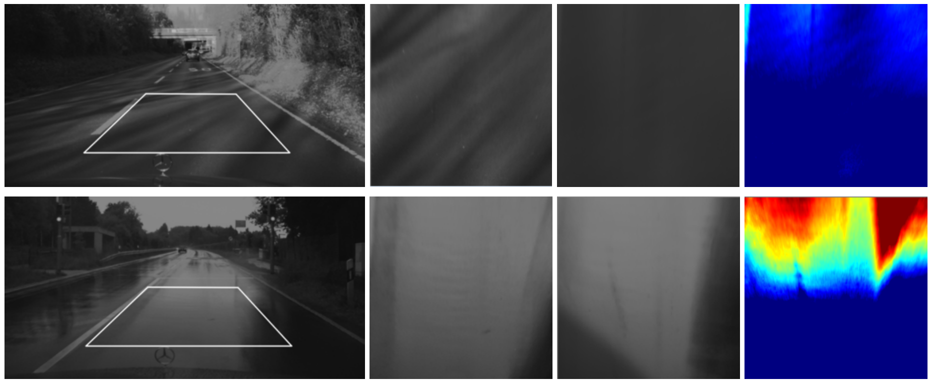
The idea we suggest in our paper is to evaluate paths of individual regions instead of regions themselves. This approach allows for accurate detections of different reflection types even during severe unregistered movements of the car. Note, that the following method is based on the introduced top view transformation (*cf.* Subsect. 3.2).

Let us assume an almost linear motion of the vehicle. Then, an individual point on the surface will pass the region of interest through a single image column of the transformed top view image. Hence, potential appearance variations can be detected not by tracking the region directly but by assessing the path of the region, *i.e.* the same image column of consecutive frames. To obtain one image including those temporal information an average image $\overline{I}_t$ is computed by

$$\overline{I}_t = \alpha \cdot \overline{I}_{t-1} + (1 - \alpha) \cdot I_t. \tag{2}$$

To be able to emphasize recent events we make use of the moving average controlled by the parameter α. Furthermore, only one single image has to be kept in memory which is of great benefit regarding embedded systems. By subtracting the column average from each point of the average image $\overline{I}_t$ reflection types can be distinguished by the resulting *specular reflection map* given by

$$\mathit{SRM}_t(x, y) = \overline{I}_t(x, y) - \frac{1}{K} \sum_{k=0}^{K} \Big(\overline{I}_t(x, k) \Big). \tag{3}$$



(a) Original image (b) I_t (c) $\overline{I}_t$ (d) SRM_t

Fig. 3. Examples for reflection modeling based on *specular reflection maps*. The first row shows an example taken from a dry road. In the second row an instance of a wet road is presented. The pipeline for reflection detection is depicted for an image (a) which was transformed into a top view (b). The averaged frame (c) is computed based on previous frames which results finally in the corresponding refection map (d).

The idea is that diffuse reflections, *i.e.* without appearance variations, have similar values along the corresponding image column in $\overline{I}_t$. Thus, subtracting the column average leads to small values for most of the surface points. In contrast, specular reflections provide severe appearance changes and the related image column of $\overline{I}_t$ yields high variance resulting in high values for SRM_t. In Fig. 3 the different stages of our approach can be seen for two examples showing dry and wet asphalt. The resulting reflection maps clearly show the indication for the described reflection types and in consequence the different road conditions.

To finally obtain features based on the computed *specular reflection map* (SRM_t) several methods can be applied. As presented later (*cf.* Subsect. 4.2) we use texture description based on *Local Binary Patterns* (*LBPs*) [14] in order to extract discriminative features for dry and wet road conditions.

The major advantage of our proposed method is that no expensive tracking of individual regions or an image registration technique is required. Furthermore, our method only needs to compute simple image averages and subsequent subtractions. Hence, results can be computed very efficiently while being robust against unregistered movements in contrast to the physical model described in Subsect. 3.2.

4 Road Condition Estimation Framework

Since the main goal of this work is to estimate the actual road condition, a common classification framework is utilized. The processing pipeline consists of three stages, namely the selection of a region of interest, the extraction of appropriate features, and finally the classification into road condition classes. In the following each of these essential steps is explained in detail.

4.1 Region of Interest

To obtain suitable feature vectors, describing a specific image region, the shape and size of this region has to be defined in advance. In [2] it was shown that road-only parts can be determined optimally by *semantic segmentation*. For our method, however, the region is limited to a simple and static geometric shape since we focus on feature extraction as well as the classification process. As already mentioned in Sect. 3, a favorable shape of this region would be a trapezoidal one, since the required rectangular top view image can be obtained based on an estimated homography. In our setup the homography is assumed to be fixed, although the ground-plane changes due to small vertical movements of the car.

4.2 Feature Extraction

Once the region of interest is defined, features can be obtained from the covered area to describe the underlying road condition. Several feature types have been investigated during the past and we found two very crucial feature types for the task at hand. In the first place, the novel *specular reflection maps* introduced in Sect. 3.3 which aim to detect specular reflections are an essential resource to distinguish between dry and wet road conditions. Secondly, texture features have proven to be most suitable to describe characteristic structures caused by wheel tracks on wet asphalt or on snow-covered roads.

Specular Reflection Maps Based on a quantitative analysis–which is not presented in this paper due to the limited space–we found that texture description methods are most suitable to cover meaningful information provided by the *specular reflection map*. Thereby, unique patterns induced by the presence of wet areas can be recognized in a very robust manner. As shown in the next paragraph *LBPs* are a prominent approach for the task of texture description. For our scenario of reflection maps it is superior in terms of accuracy to other state-of-the-art approaches such as GLCMs [4]. Additionally, those descriptors can be computed very efficiently which is a crucial factor when implemented on embedded systems.

Texture Description Since sole reflection modeling is not sufficient to distinguish between dry and snow-covered areas, texture description on the original image became the second key element. Here, characteristic structures on the lane provide useful information about the present road condition. As already mentioned in the previous paragraph *LBPs* have proven to be the most suitable texture description approach for the task at hand. The reasons for that are twofold: On the one hand, *LBPs* can be computed very efficiently which is as beneficial as crucial while running on an embedded environment. On the other hand, it is highly discriminative in contrast to other fast texture recognition methods. As we are interested in the texture of the actual road surface, a cropped version of the original image is transformed into a top view image (*cf.* Sect. 3). We limit ourselves to the intensity channel of the HSI image representation, since color information is prone to color shifts (*e.g.* different colored windshields).

4.3 Classification

The final step in our framework is the classification into road condition classes, namely dry, wet, and snow-covered. We have decided for *Extremely Randomized Trees* [3] as a prominent non-linear classifier for two reasons. On the one hand, the implementation is highly memory efficient in contrast to comparable methods like Nearest-Neighbor classifier. Only some simple thresholds have to be kept in memory instead of entire highly dimensional feature vectors of some or even all training samples. On the other hand, the computation time during classification is very low based on only few and simple numerical comparisons. Both advantages make *Extremely Randomized Trees* highly preferable for our task.

5 Experiments

In the following, we present evaluations of our proposed method which are based on a huge real-life data collection acquired over the past 18 months. The dataset comprises a variety of environmental settings such as motorways as well as urban and suburban scenes at different locations from all over Germany as well as from Sweden. We use a total of $\sim 3,500$ sequences resulting in $\sim 150,000$ single images each with a resolution of 1076×648 pixels at a frame rate of 16 fps. Ground-truth data was provided for all sequences by an human expert during the acquisition including the unique labels *dry*, *wet*, and *snow-covered*. Additionally, intermediate labels are assigned to sequences which show mixed conditions and transition between unique classes which are not considered for this evaluation. The overall distribution of class labels is given by 60% showing dry, 14% showing wet, and 26% showing snow-covered conditions. Example images for each road condition class can be seen in Fig. 4. For the evaluation we conduct a 10-fold cross validation where only 10% of the data was used for training and the remaining 90% for testing. Overall and average recognition rates were used in order to measure the classification performance sample-wise as well as in a class-wise manner. We compare our proposed method to state-of-the-art techniques and provide a simple baseline approach developed during a preliminary study of this work. It is shown that our method outperforms all other methods despite of challenges, *e.g.* color shifts, under- and over-exposed images, severe reflections due to low sun, and even image artifacts caused by erroneous demosaicing [11]. In the course of a parameter evaluation–which is not presented in this paper due to the limited space–we found the most suitable setting given by $\alpha = 0.05$, $P = 8$, $R = 1, 2, 4$. Thereby, an increasing value of α would lead to erroneous estimations caused by short-term disturbances whereas smaller values would cause a delayed recognition of an actual change of the road condition. As presented in [14] the number of neighbors is set to $P = 8$ to ensure an efficient implementation by using an 8-bit data type. The corresponding radius R has been set to different distances to obtain a pyramidal representation. As suggested in [3] an ensemble size of 100 trees was selected for the classification.

5.1 Evaluation and Comparison

Since there is no commonly used dataset for the task of road condition estimation and sources of other methods are not publicly available, works of [9, 15, 22] have been

Table 1. Comparison of various camera based methods for road condition estimation.

METHOD	DRY	WET	SNOW	ARR	ORR
Baseline	82.71	75.22	64.24	74.06	77.33
Kawai *et al.* [9]	42.03	52.56	79.25	57.95	55.55
Sun *et al.* [22]	70.23	91.31	76.35	79.30	74.95
Omer *et al.* [15]	96.85	79.89	95.49	90.74	94.25
Ours	98.90	93.17	94.93	95.67	96.84
Ours + context	**99.44**	**93.50**	**97.84**	**96.79**	**98.09**

reimplemented. This allows us to compare the performance of our proposed method with recent works in this field of research. Additionally, we present results produced by a baseline approach developed during a preliminary study.

In Table 1 the recognition rates for our approach as well as for works of [9, 15, 22] are presented. As can be seen our method is superior regarding each condition class which results in a substantial increase of overall and average performances. The system of [22] which is solely based on GLCM texture modeling is capable of detecting wet conditions, but shows poor results for dry and snow-covered scenes. Our implementation of [9] provides rather poor results for all classes and has the additional disadvantage of high computational costs, *i.e.* 12 seconds per frame, which renders the method useless for real-time applications. In contrast to that, [15] provides high recognition rates for snow-covered and bare roads for which the method was initially designed. This strength can be explained by the fact, that they use context information from non-road parts by considering the entire lower image region. Additionally, the usage of color information is very useful as long as the setup does not change, *e.g.* by differently colored windshields or unexpected illumination changes. Although our method produces slightly worse results for snow-coverage compared to [15], it was possible to obtain superior overall as well as average recognition rates while still considering only-road parts without using color information. As a further improvement of our approach, the entire lower image region was considered to cover useful information about saturation and intensity variations between road and non-road parts. The idea is that snow-covered areas yield low variances in the saturation channel whereas bare road scenes show high variances caused by road-markings and grass verges. The resulting performance gain can be seen in the last row of Table 1.

The major advantages of our proposed approach is the ability to distinguish between all potential road conditions in a very robust manner without the sensitivity to color and illumination changes. Furthermore, the actual runtime, *e.g.* at least 16 fps, renders our method suitable for real-time applications. In Fig. 4 qualitative results are presented for each road surface condition class showing the advantages of our method.

Limitations of our approach appear when driving through narrow bends as the method assumes an almost linear motion. This drawback can be resolved by an adaptation of the static homography in terms of aligning the top view image in the direction of motion. Furthermore, disturbances on the windshield, *e.g.* contamination and reflections caused by the car's hood can result in erroneous estimations. In addition, varying

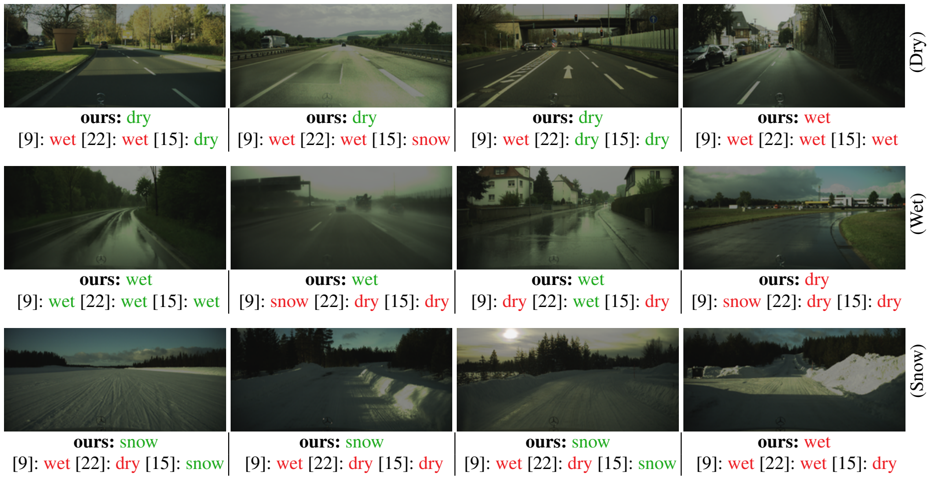


Fig. 4. Qualitative evaluation of our approach compared to Kawai *et al.* [9], Sun *et al.* [22], and Omer *et al.* [15]. Results are highlighted below each image (best viewed in color).

exposure times of the camera can lead to changing appearance of individual regions which can be rectified by taking the corresponding value into account.

5.2 Computation Times

The presented road condition estimation framework was solely implemented in C/C++ using the OpenCV library 2.4.9. Similar to the computer setup of the demonstration vehicle an Intel® Core™ i7-2600 standard desktop computer @3.40 GHz was used for our experiments. The computation time for one single frame was approximately 50 ms which guarantees real-time capability of our approach, *i.e.* 16 frames per second.

6 Conclusions

In this paper we presented a fast and robust approach for the task of road condition estimation based on a monocular camera. Motivated by a physical reflection model a transformation of the input image into a reflection map was proposed. Feature vectors were obtained by the extraction of texture features based on the reflection map as well as on the original image. Afterwards, a standard classifier was applied which meets the special requirements of embedded systems. Based on a large and challenging dataset it was possible to show that the proposed method clearly outperforms other vision-based state-of-the-art methods. The main advantages of our approach are the capability of running in real-time as well as the robustness against diverse disturbances in contrast to standard reflection modeling based on image registration and tracking.

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