Towards Reliable Traffic Sign Recognition

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***Abstract*—The demand for reliable traffic sign recognition (TSR) increases with the development of safety driven advanced driver assistance systems (ADAS). Emerging technologies like brake-by-wire or steer-by-wire pave the way for collision avoidance and threat identification systems. Obviously, decision making in such critical situations requires high reliability of the information base. Especially for comfort systems, we need to take into account that the user tends to trust the information provided by the ADAS [1].**

In this paper, we present a robust system architecture for the reliable recognition of circular traffic signs. Our system employs complementing approaches for the different stages of current TSR systems. This introduces the application of local SIFT features for content-based traffic sign detection along with widely applied shape-based approaches. We further add a technique called contracting curve density (CCD) to refine the localization of the detected traffic sign candidates and therefore increase the performance of the subsequent classification module. Finally, the recognition stage based on SIFT and SURF descriptions of the candidates executed by a neural net provides a robust classification of structured image content like traffic signs. By applying these steps we compensate the weaknesses of the utilized approaches, and thus, improve the system's performance.

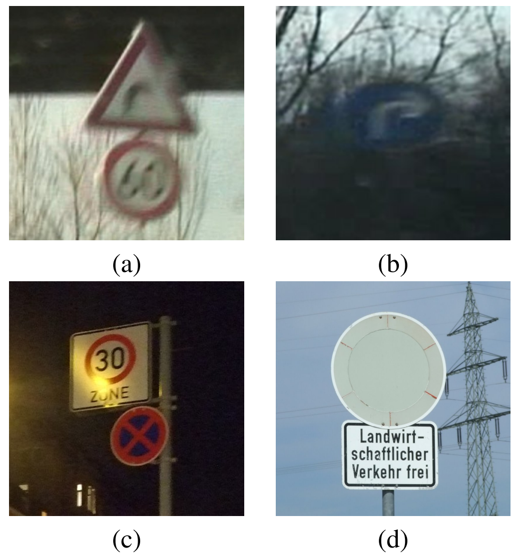


Fig. 1. **Examples for challenging recognition conditions.** (a) Motion blur due to long exposure time, (b) low contrast to background, (c) highlight and color shift on the top sign, (d) colors degraded by sunlight. (a) & (b) are examples from the sequence used for the system evaluation.

I. Introduction

Former driver assistance systems have strongly focused on the improvement of the driving quality and comfort. With increasing computing power and the availability of high quality sensors the safety aspect of ADAS gained more and more attention [2].

The task of driving a car is based to a large extent on visual information processing. Important information about the traffic situation is presented to the driver encoded as visual signals like traffic signs, traffic lights, road markings, etc. Many accidents result from misinterpreting or ignoring this information as shown in [3]. To increase safety, an ADAS has to understand this visual language using different approaches including traffic sign recognition (TSR). [4] states that the largest improvement on safety could be reached by those ADA systems that take into account the information provided by TSR. Although the appearance of the traffic signs was originally designed to be easily distinguishable from natural objects, the reliable, automated recognition of the traffic signs, especially under severe environmental conditions, remains a complex task. In Fig. 1, some degraded signs are shown which underline this general statement.

II. Related Research

The first research on TSR goes back into the 80s, when Akatsuka and Imai worked on an early system for computer-based traffic sign recognition [5]. Since then a lot of research activities have taken place. Most of them were strictly bound by the available computing capacity, e.g. in [6], where an optical filter was used for color segmentation to avoid the high amount of data when processing color images.

Recent approaches on TSR tend to use a scheme of 3 stages: i) localization/detection of sign candidates, ii) classification of the candidates and iii) tracking of the traffic sign candidates over time.

Detection: Many TSR systems are using color segmentation for a preliminary reduction of the search space and apply algorithms like color thresholding [7], [8] or the Bayesian classification of the color [9]. The adapted color space seems to be more or less a question of faith (RGB: [7], [9]; HSV: [10]; YUV: [8]; L*a*b: [11]).

Another commonly used approach for the detection of traffic signs is the search of their distinctive shapes, which can be easily differentiated from natural objects due to their artificial appearance. An intuitive approach on shape detection is pattern matching as utilized in [7]. Liu and Liu instead adapt a Genetic Algorithm to search for circular shapes [12]. But probably the most favorite algorithm applied to shape detection is the Hough transform and its derivatives [13], [14]. Especially, the fast Hough transform for circles published in [13] and its generalization [15] are widely applied. Local features represent the third major concept to detect road signs within traffic scenes. [16] localizes "good features to track" and adapts the Gaussian Mixture Model of the regional hue as feature descriptor. Other recent approaches ([17], [18]) exploit the strengths of rectangle features in combination with AdaBoost and a hierarchical structure of classifiers as introduced by Viola and Jones in the context of face detection [19].

Classification: There exist different ways to recognize the detected sign candidates. One of them is to apply the methods of OCR/ODR (optical character/digit recognition) systems, as in [16], [20]. Another approach uses the pictogram-based classification of the traffic signs by template matching or cross-correlation ([11], [13]). In [17] and [14], the authors make use of the LDA to distinguish between the road signs. Furthermore, [21] introduces a biologically inspired approach which uses a neural net hierarchy with memory. Thus, there is no clear-cut choice for the discriminative learner. Within the current approaches, the Multi-Layer Perceptron [8] is a widely spread option. The Support Vector Machine also plays an important role because of its strength against overfitting [22].

Tracking: To increase the robustness of TSR, many systems rely on tracking to maintain a road sign candidate over time. In this way, misinterpretations of the candidates can be reduced. The most common tracker adapted to the TSR problem is the Kalman filter and its modifications, as utilized in [23].

III. Proposed Method

Traffic sign recognition, as a foundation for several ADAS, has to be reliable and robust. We propose a system built in accordance with the three common layers current TSR systems provide - as depicted in Fig. 2. In addition to these layers, we introduce a fourth stage between detection and classification: the refinement stage. At this point the location estimates of the detected candidates are refined to facilitate the classification process.

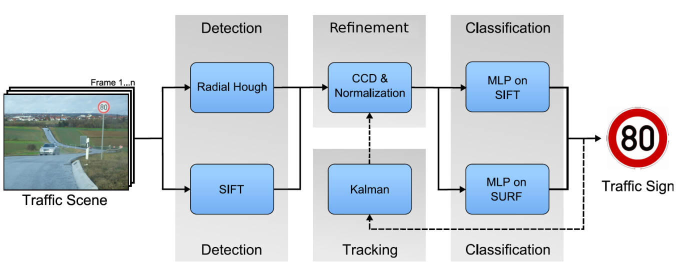


Fig. 2. **Structure of the proposed system for traffic sign recognition.**

As Figure 2 points out, we do not rely on color segmentation. Although this is a fast and fair method (due to the choice of the colors that traffic signs contain - which are separable from natural objects and commonly show good contrast to the background) there is no applicable color constancy algorithm to retrieve a robust result [24]. A reliable color segmentation in scenes, where the spectra of the light sources are unknown, is impossible to achieve without a color constancy, similar to the one human perception offers. In [7], Broggi reports problems caused by a chromatic shift of the image due to lighting. Nevertheless, his solution using a color equalization algorithm based on the color assertion of the street is generally not applicable (e.g. due to multiple light sources, color variations of the pavement). To increase the system's reliability, we adapt two different algorithms for the detection and the classification stage. These algorithms are intended to complement each other. Circular Hough transform is for example a very strong detection algorithm for round traffic signs. However, in cases where we have low contrast between the road sign and its background a gradient based algorithm yields a poor performance. This problem has already been mentioned in [14]. To compensate for this our second algorithm based on local SIFT features allows the correct detection of the traffic sign by identifying the sign's content. On the other hand the SIFT detection is strengthened by the shape-based approach which shows great robustness on small resolutions and strongly blurred input data.

A. Detection

As mentioned above, we apply a twofold detection stage.

Shape-based detection. The first part utilizes a fast implementation of the Hough transform for circles based on the algorithm published by Barnes and Zelinsky [13]. The size of the three-dimensional accumulator space matches the size of the input video sequence (640x360px), and the radii of 4 to 30 pixels we want to cover. The radius interval is restricted by the maximum size of a traffic sign's appearance in a road situation regarding the mentioned resolution, and by the minimum radius, at which a classification algorithm could properly distinguish between different signs. After the accumulator space is initialized by voting for every gradient pixel of a single frame along its gradient direction, the detected circles are extracted. We keep the number of circles low due to the high computational power needed for the following stages. In the case of blur or surface shading, the vote of a circle is often smeared. To avoid extraction of multiple circles for one round shape, we apply a regional suppression in a rectangular neighborhood with the size of $2r+1$. The available color information is used to receive a more robust detection of circles by introducing additional color gradients.

Content-based detection. An approach based on local features has been adapted to the TSR problem as the second algorithm within the detection stage. Based on local image descriptors, traffic signs are detected by means of their content, hence complementing the shape-based approach. After the evaluation and testing of several local feature detectors and descriptors (among them SIFT, USURF-128, GLOH) on different traffic scenes, SIFT (Scale-invariant feature transform [25]) turned out to be the most suitable one for reliable TSR.

To compare the extracted descriptors, we use the nearest neighbor distance matching scheme, which, as mentioned in [26], provides the highest precision among the evaluated ones. This means that two descriptors v, w_1 are considered as a match if they fulfill (1), where w_1 and w_2 are the feature vectors of the traffic scene with the smallest and second-smallest Euclidean distance to the SIFT-feature v from the traffic sign reference image. For the ratio threshold, a value of $\sigma_{ratio} = 0.75$ turned out to be the best for several local feature approaches using the Euclidean distance metric.

$$|\mathbf{v} - \mathbf{w_1}| \,/\, |\mathbf{v} - \mathbf{w_2}| < \sigma_{ratio} \tag{1}$$

We use SIFT as a region detector to localize potential road sign candidates within a traffic scene. Therefore, SIFT features of the traffic scene and of reference traffic signs are calculated and compared with each other. The number of extracted descriptors depends on the amount of details in the image. This results in a strong correlation with the image resolution for most natural images. To overcome problems with the large number of descriptor comparisons and indiscriminative features at certain scales, we select a small set of robust features with high matching performance, an approach which is beyond the scope of this paper.

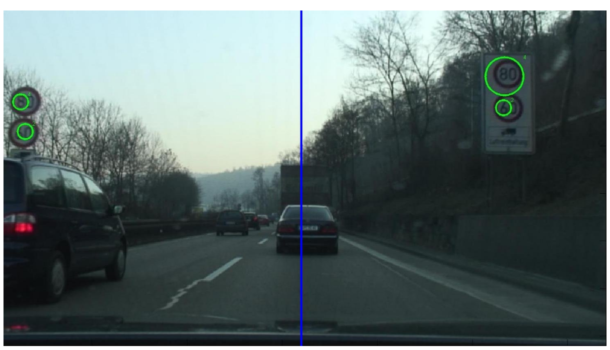


Fig. 3. **Example of candidate regions detected by clustered local feature matching.** The blue line indicates the slice distinction.

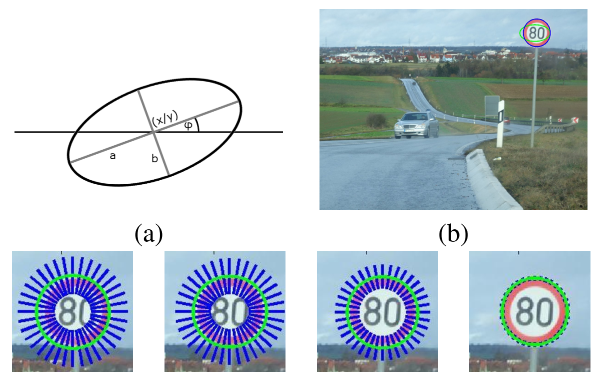
Finally, traffic sign candidates are extracted from the clusters of the best matched descriptors together with their position and scales. Fig. 3 shows a typical result of the proposed local feature detection. As can be seen from this example, a refinement step before the classification is necessary to improve the candidate's location and thus to get feasible segmentation results. Traffic signs of the same type inhibit each other's matching performance when searching them by using the local feature approach. Hence, we introduce a simple image slicing technique to avoid this obstacle (the blue line in Fig. 3 depicts this slicing).

A final classification to traffic sign classes based on the matching results does not take place. We use SIFT to locate the sign candidate, only. The available information of the candidate's class affiliation is processed as hint within the subsequent classification stage. Thus, ambiguities across traffic signs have a marginal effect.

B. Refinement

Within the refinement stage, the position and scale estimates of the detected sign candidates are processed by the Contracting Curve Density (CCD) algorithm [27]. This leads to a uniform candidate segmentation and reduces the impact of perspective projection, image blur and general errors in the position/scale estimation, as they are common especially for the applied local feature approach (see Fig.3).

Since we focus on the detection of round traffic signs in this paper, an elliptical active curve model is used as depicted in Fig. 4(a). The original CCD approach is a computationally complex algorithm. Hence, we use the more convenient real-time adaptation of the CCD algorithm described in [28].



(a) (b)

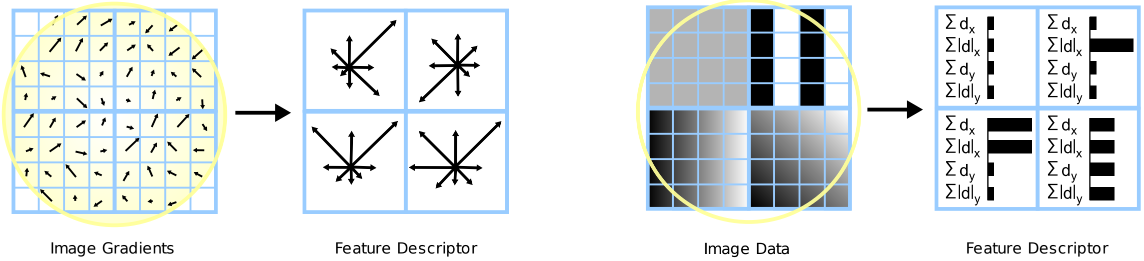
(c)

Fig. 4. **Application of the CCD algorithm.** (a) Used parameter model for the active curve. (b) Example of CCD segmentation. (c) Stepwise processing and curve estimation improvement.

Contour approximation of the active curve in the CCD algorithm is done by stepwise minimizing an energy function based on the local color statistics of both sides of the curve. This iterative process is illustrated in Fig. 4(c). The approximated curve vicinity, which is the source for the local color statistics, is represented by the blue lines. The considered vicinity depends on the curve estimation and hence decreases in size with the variance implied by the curve statistics. The mean of the estimated curve parameters is shown with a green ellipse. In Figure 4(b) an example of the CCD application is shown where the green ellipse is the initial curve approximation and the blue one represents the candidate region after CCD-based segmentation. Finally, the size of the candidate region is normalized for further processing steps.

C. Classification

The recognition stage we use in the proposed TSR system consists of two Multi-Layer Perceptrons (MLP). They classify the sign candidates delivered by the refinement stage in parallel by means of two different features. The first one is to a large extent similar to the SIFT descriptor [25]. The feature used as input for the second MLP is based on the Speeded-Up Robust Features (SURF) descriptor introduced in [29]. Both feature descriptors are calculated directly on the candidate regions. This means that no keypoint detection is performed.



(a) (b)

Fig. 5. **Utilized features for classification.** The feature vectors are built on locally segmented, gaussian-weighted histograms: (a) Scheme of the SIFT descriptor. [25] (b) Scheme of the SURF descriptor. [29]

The SIFT descriptor can be considered as a set of spatial distributed gradient orientation histograms. The design of this descriptor is displayed in Fig. 5(a) according to [25]. In contrast to the original approach, the orientation assignment step is omitted due to the fact that traffic signs can be asserted to be always vertically oriented with respect to the road surface, especially by taking the gradient sampling of the descriptor into account.

SURF features are largely inspired by the SIFT approach. Among other common steps, both descriptors reduce the spatial information by applying statistical methods on regional partitions. In contrast to gradient orientation histograms like the ones the SIFT descriptor uses, the SURF descriptor is computed by summing up the responses of the Haar-Wavelet base functions in horizontal and vertical direction. The structure of the SURF descriptor is represented by Fig. 5(b).

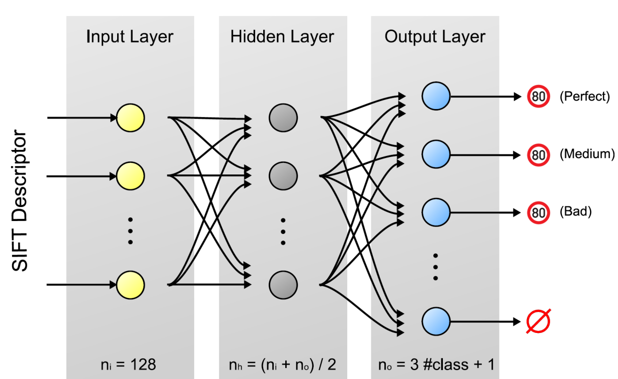


Fig. 6. **Structure of the utilized MLP.**

For the recognition we rely on a MLP to distinguish between several traffic sign classes. The input layer of this neural net consists of 128 neurons reflecting the dimensionality of the feature vector. The output layer represents every traffic sign class by a neuron. Moreover, not only the class of the road sign has to be determined, but also the quality of the candidate's segmentation. This allows us to make assumptions on the classification performance based on previously gathered statistics. We distinguish between three different segmentation quality levels: perfect, medium and bad. Since we also would like to differentiate between traffic signs and candidates containing a false detection, we define an additional "not a sign" class. In Fig. 6 an overview of the feed-forward MLP structure is given. We apply one hidden layer to the MLP and fix its number of neurons n_h to $n_h = \frac{(n_i+n_o)}{2}$, which turned out to work well for our experiments. n_i is the number of neurons of the input layer and n_o of the output layer, respectively.

Feature /	Test Dataset		
Segm. Quality	Perfect	Perfect-Medium	Perfect-Medium-Bad
PCA	96.5%	88.2%	85.1%
SIFT	100%	98%	95.7%
SURF	98.7%	97.2%	95.7%

TABLE I
RIGHT CLASSIFICATION RATE FOR THE SIGN:NOSIGN PROBLEM ON TEST DATA WITH DIFFERENT SEGMENTATION QUALITY.

The strength of a classification method based on an MLP with the proposed features especially unfolds when recognizing well segmented and highly structured traffic signs. A hint about the performance is outlined by the following (see Table I) simple evaluation of a two class separation problem (sign or no sign). Here we use a test set of about 500 traffic sign examples of the three segmentation qualities and compare the results to an MLP trained on PCA-transformed candidate regions. It is remarkable that using the SIFT descriptor we retrieved a 100% correct classification rate considering only perfectly segmented candidates.

D. Tracking

To improve the recognition results it is common and advisable to utilize the temporal dimension and maintain the traffic sign candidates over time. We apply a discrete Kalman filter similar to other recent approaches. For each sign candidate the position and scale parameters are tracked. This is done in image space for simplicity reasons. Leading us to four parameters $(pos_x, pos_y, scale_x, scale_y)$ to be handled. These parameters are tracked using a Kalman filter up to the 3rd order. The Kalman filter, as depicted in [30], is used to estimate the state of a linear system in a recursive manner. We use a simplified linear system model according to (2) and (3) as the base for our Kalman filter.

$$\mathbf{x_t} = \mathbf{A}\mathbf{x_{t-1}} + \mathbf{w_{t-1}} \tag{2}$$

$$\mathbf{z_t} = \mathbf{H}\mathbf{x_t} + \mathbf{v_t} \tag{3}$$

In (2), x_t is the system state at time t. Since we use discrete time steps, t is increased by T which is directly correlated to the video frame duration. The measurement z_t depends on the mapping of the true state x_t according to the observation model H. w_t and v_t are zero mean, normal distributed random variables representing the process noise and the measurement noise respectively. An example of the state transition matrix A and the state x_t is given in (4) and (5) for parameter pos_x.

$$x_t = \begin{pmatrix} pos_x(t) \\ \dot{pos}_x(t) \\ \ddot{pos}_x(t) \end{pmatrix} \tag{4}$$

$$A = \begin{pmatrix} 1 & T & \frac{T^2}{2} \\ 0 & 1 & T \\ 0 & 0 & 1 \end{pmatrix} \tag{5}$$

Between the prediction step and the update of the Kalman filter, the candidates are assigned to the tracked traffic signs according to Fig. 7.

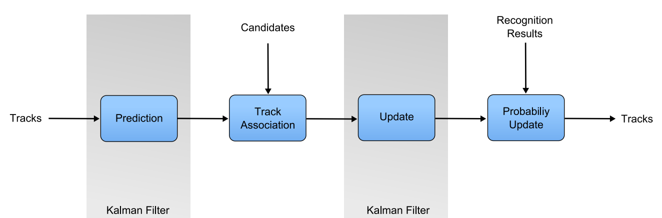


Fig. 7. **Scheme of the tracking process.**

Tracks are associated using a scalable prediction window based on the estimated traffic sign size and the velocity vector of the tracked candidate prediction $\dot{pos}(t^-)$ as shown in (6). In our case, we found the parameters $\tau_1 = 2.5$ and $\tau_2 = 25$ to work well.

$$wscale = \left(\tau_1 scale(t^-) + \frac{\dot{pos}(t^-)}{\tau_2} \right) \tag{6}$$

To avoid incorrect assignments between tracks and candidates, it is necessary to check the plausibility of the track-to-candidate correspondence. Since the match with the prediction window does not solely suffice, the plausibility is checked by a rule-based approach utilizing combined distance and direction differences of the detected candidate and the track prediction. In this way we can overcome assignment problems that arise from road signs stacked on one pile (see Fig.3 for an example).

The classification results of a tracked candidate are merged over several time intervals by the summation of the class scores. An output is not generated until a reasonable certainty about the candidate's class affiliation is reached. This involves a selection scheme quite similar to the nearest neighbor distance matching strategy we also use for the local feature matching.

IV. Evaluation

For evaluation we judge the detection and classification performance by means of $Recall$ and $Precision$ (7) and (8) - terms used in the field of Information Retrieval. Since a detection could be considered as a classification of pixel blobs into candidate or non-candidate classes this rating scheme is applicable to the evaluation of the detection performance, too.

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

The metric is defined by the number of true positive (TP), false negative (FN) and false positive (FP) classifications. Recall is also known as true positive rate or as detection rate in the context of the detection stage evaluation.

We evaluated the system performance by recognizing the traffic signs in a 30 minutes sequence. The sequence was captured while mainly driving on a highway and to a small extent in urban traffic. The camera was mounted towards the driving direction behind the front windshield. The test sequence contains 133 traffic signs (excluding signs that are too far away or do not belong to the official traffic rules). 94 of these signs are relevant to the driver, i.e. the driver is supposed to recognize them. Two of them are depicted in Fig. 1.

	#Signs	Detection Rate	Frames (∅)	Perf. Segmented
All	133	97%	33.9	65.11%
Relevant	94	**100%**	38.5	65.35%

TABLE II
Performance of the detection stage. Results distinguished by relevance to the driver.

The relevant traffic signs must be detected and correctly classified by a reliable TSR system. Table II shows the results of the detection stage for this sequence. Beside the aforementioned detection rate, the number of frames in which a traffic sign is detected on average is provided, too. As Table II points out all traffic signs relevant to the driver were detected. In average a relevant traffic sign was detected over 38 times from its first appearance until leaving the scene (varying between 6 and 271 detections).

	#Signs	Recall	Recall w/o untrained	Precision
All	133	74.8%	81.4%	70.8%
Relevant	94	86.2%	**96.4%**	68.1%

TABLE III
Performance of the proposed TSR system. Results distinguished by relevance to the driver. Includes detection, refinement, recognition and tracking stage.

Due to the introduction of the refinement stage an optimal segmentation of approximately two-thirds of all candidate regions was observed. A detailed evaluation of the CCD performance resulted in the fact that in case of the candidates provided by the Circular Hough transform, 79.3% of the traffic sign locations were improved (6.9% worsened), whereas, 63.6% of the SIFT detections - which were initially poorly located - were refined by position and scale (15.2% worsened).

The entire system's performance is given in Table III including Recall and Precision of all 4 stages of the proposed TSR approach. With the "Recall w/o untrained" value, the adjusted performance rating is provided considering only the 15 traffic sign classes for which we have trained our classifier. The results reveal that a high recognition rate is achieved regarding a realistic test sequence with varying light conditions.

V. Conclusion

In this paper, we proposed an approach for reliable traffic sign recognition based on the 3 common stages of recent TSR systems which are detection, classification and tracking. We added a fourth stage, that we called refinement stage, where we improved the localization of the detected traffic sign candidates using a fast version of the CCD algorithm. Furthermore, we suggested the use of complementing algorithms within the detection and classification stages. Additionally, we introduced a SIFT based detection module and a recognition module on the foundation of SIFT and SURF descriptors. The system was evaluated using a 30 minute long test sequence containing 94 signs that are relevant to the driver. All(100%) of these signs were extracted by our detection module from which 96.4% were correctly identified. Further steps would include the detection and classification of non-circular signs. All introduced algorithms are easily extensible to this task. Future work also would investigate the use of a better complementing feature for classification, other than the SURF descriptor. Finally, extensive tests, including other challenging scenarios like different weather situations, will also be taken into account.

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