Highway Traffic Classification for the Perception Level of Situation Awareness

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Abstract. The automotive industry is rapidly moving towards the highest level of autonomy. However, one of the major challenges for highly autonomous vehicles is the differentiation between driving modes according to different driving situations. Different driving zones have different driving safety regulations. For example, German traffic regulations require a higher degree of safety measurements for highway driving. Therefore, a classification of the different driving scenarios on a highway is necessary to regulate these safety assessments. This paper presents a novel vision-based approach to the classification of German highway driving scenarios. We develop three different and precise algorithms utilizing image processing and machine learning approaches to recognize speed signs, traffic lights, and highway traffic signs. Based on the results of these algorithms, a weight-based classification process is performed, which determines the current driving situation either as a highway driving mode or not. The main goal of this research work is to maintain and to ensure the high safety specifications required for the German highway. Finally, the result of this classification process is provided as an extracted driving scenario-based feature on the perceptual level of a system known as situation awareness to provide a high level of driving safety. This study was realized on a custom-made hardware unit called "CE-Box", which was developed at the Department of Computer Engineering at TU Chemnitz as an automotive test solution for testing automotive software applications on an embedded hardware unit.

Keywords: Situation Awareness · German Highway · Traffic Light · Speed Limit Signs · Computer Vision · Machine Learning

1 Introduction

The issue of accurate driving scenario perception plays a significant role in the avoidance of accidents and traffic control. Driving scenarios differ with the change of driving modes. Safety rules and regulations also have a distinct level of priorities based on various driving modes. The different countries enforce distinct rules and regulations in order to establish the safe driving situations. For the purpose of the research of this study, the German Highway traffic system has been considered. The German highway system, having permission for high driving speeds is a more critical location than others [2]. According to the German Statistics portal [3], around 90 percent of accidents involving passenger cars happened in the location of German highways and Motorways. This is happening even after the German highway is considered as one of the safest in the whole world [4]. This highlights the significance of understanding the driving scenarios as we move towards higher levels of autonomy. An accurate classification system to classify German highway driving scenarios could be essential for highly autonomous vehicles to automate the safety measurements and maintain a low level of accidents.

Vision-based approaches are becoming an impressive area for more and more researchers to co-operate with the automotive industry to make traffic environments safer. The classification of the German highway is a very special problem due to the reason of not having a standard definition. German traffic rules and regulations have some specifications for different driving locations and modes [2]. Based on these specifications, a classification system is proposed in this research work, which consists of three sub-systems. These different sub-systems were created based on the recognition of traffic lights and traffic speed signs. An additional recognition system was developed to detect some German highway specific signs.

Due to the lack of standardized specifications regarding traffic lights, perception becomes a very special problem. Although generalizing traffic lights becomes difficult, it is possible to recognize using specific techniques. Recognition of Traffic signs on the other hand comes with different challenges due to the variety of traffic signs. This problem could also be solved when machine learning or deep learning techniques are applied. With the emergence of image based system, this paper focuses on the camera sensor, using image processing and machine learning techniques to recognize traffic speed signs and lights.

German highway driving scenarios have also consisted of several highway specific traffic signs. These signs are specific to the German highways. Hence, a custom image processing algorithm is additionally developed to recognize some of these specific signs which detected the German highway route numbers and the direction of the route.

In recent times, the term situation awareness is attaining a lot of popularity in the automotive industry [16]. According to the pioneer of situation awareness, Endsley M.R., situation awareness means to extract and perceive information as features from both internal and external environments, provide understanding towards the perceived information, take actions and predict states based on the taken actions [1]. The classification system proposed in this paper is provided to the perception level of situation awareness to analyze the overall situation.

In this paper, a weight-based classification system is proposed to classify the German highway driving scenarios. Although the deep learning techniques like SSD, FRCNN, YOLO capable in providing the accurate results, they also requires high level processing unit as well. Hence, keeping the target hardware into consideration the implementation of three sub-systems was carried out using machine learning and image processing approaches. It focuses on the contours-based ellipse fitting technique to detect the circles of speed limit signs, blob detection technique for detecting the traffic light shapes, contours, and scan line method for detecting the German highway route numbers and Hough line transformation for detecting the directional signs. The "CE-Box" was one of the hardware units from TU Chemnitz that was used for the testing of the implementation [6].

2 State of the Art

2.1 Situational Awareness

The major concern in the system operation is situation awareness which plays a significant part in making decisions based on the persuasive view of the diverse state [1]. Primarily consider the factor from the environment which helps to bring awareness of the current situation. The situation awareness model does the sorting of errors and then the design effects are created to enhance the operations. It consists of three levels and the first level is perception, where features are extracted from the surrounding environment. The second level called comprehension gives meaning to these extracted features and can take actions on them [6] [1]. Whereas the third level works around predicting states based on the actions taken in the comprehensive levels.

2.2 Traffic Light Detection and Recognition

Philipsen M. P. et al. [7], used a learning-based method and spotlight intensity-based method to detect the traffic light. The Learning-based method involves the modified Adaboost classifier and sliding window techniques. The former method performs better concerning precision and recall. C. Chiang et al. [8], proposed a method for segmenting the traffic lights. The pixel extraction using HLS Color transformation and shape extraction using the ellipse detector of the traffic light. R. de Charette et al. [9], proposed a template matching method which classifies the traffic light with the confidence of the match with the template. Julkar Nine et al. [10], presented a method to recognize the traffic light using a monocular camera with "CE-Box" setup and "BlackPearl". Reducing the noise in the captured image, detecting the traffic light using a Laplacian edge detector, and finally, Hough Circle Transformation is used to distinguish the traffic light.

2.3 Speed Limit Sign Detection and Recognition

W. Li et al. [11], have used this RGB color space for detecting the boundary of the speed limit signs. The method extracts the individual R, G, B components from the image and then used the median filter to remove the noise from them and finally combined the components. Torresen J. et al [12], use the image filtering process based on an RGB color model for their speed limit sign detection system. Ardianto S. et al. [13], uses this HSV color space for the segmentation of the outer boundary of the sign. But before using color thresholding, the paper uses histogram equalization so that the quality of the image is improved and contrast is increased. This method is accomplished by converting the original image to YCrCb color space and then using the histogram equalization method to equalize only the luminance portion of the image. The image is eventually transformed into HSV color space for the segmentation process. And also used the SVM classifier with Histogram of Oriented Gradients (HOG) features for the recognition of limit signs. The suggested method utilizes the multiple linear SVMs for the classification purpose and also reduces the number of feature vectors to increase the speed of recognition. Miyata S. [14], also use the HSV color model for extracting the outer ring of the speed limit signs. The method uses a machine learning algorithm known as the AdaBoost classifier to find the limit signs using the features extracted from the image. The features were extracted using Local Binary Pattern (LBP) features. The benefit of using these patterns is that the features could be locally extracted from the image. Another advantage is that the features are less prone to change in the illumination conditions. Pon A. D. et al. [15] proposed an approach to train the deep learning model in a mini-batch selection mechanism to detect the traffic light and sign. One network architecture improves detection performance. However, the model does not achieve good accuracy or recall.

3 System Design

3.1 System Architecture

The sub-systems for the classification system aim to develop applications for the recognition of traffic objects in given input videos. The videos are given as the input for the system architecture layer, whereas the processed data will be provided as output from the application layer. Several algorithms are performed simultaneously to detect the German highway specific traffic signs, speed limit signs, and traffic lights. Once the algorithm detects any of these signs, it stores the detection output and provides the result to the classification system. There is an additional option available in the system to send the output as a CAN message with unique identifiers for future implementation purposes. The system architecture is presented in Fig. 1.

3.2 Software

"CE-Box" contains manifold racks of Raspberry Pi embedded with PiCAN 2 modules. The operating system used in each of the Raspberry Pi was Raspbian Stretch. Several libraries are installed such as scikit-learn, skimage, scipy, numpy, OpenCV along Python to run and test the algorithm in the "CE-Box". For the execution of computer vision application and image processing, C++ dependencies are used.

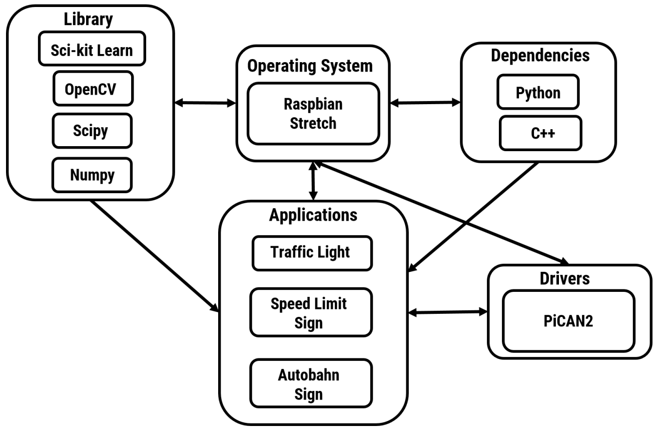


Fig. 1: System Architecture

3.3 Hardware

Julkar Nine et al. [10], have made use of a hardware component called “CE-Box” developed under the Department of Computer Engineering of TU Chemnitz for the application as shown in Fig. 2. The hardware unit consists of several racks. Each of the racks is powered by Raspberry Pi 3b+ models with embedded PiCan2 module. The racks can communicate with each other via CAN communication. This hardware setup is used to test the proposed algorithm. The input videos are processed by the algorithm in the Raspberry Pi. Then, the output of the algorithm is stored and forwarded to the classification system. It can also be provided as a CAN message with unique identifiers to PiCAN 2 for future implementation purposes. The PiCAN 2 can communicate with ECU through CAN message. Through the screw terminal or DB9 connector, PiCAN 2 is powered and Python is used as the programming language.

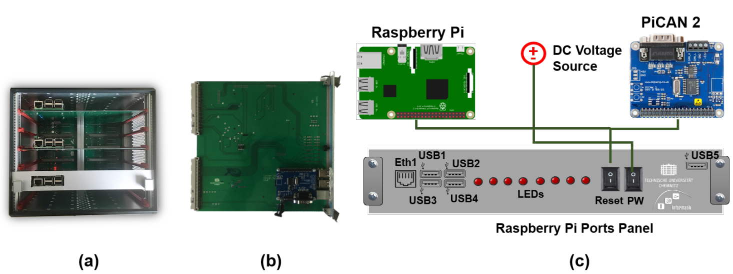


Fig. 2: System Setup: (a) CE-Box Top View, (b) CE-Box Rack, (c) CE-Box Connection (Front Panel) [10]

4 Implementation

The German highway is classified based on the information gathered from three different detection systems. Therefore, one of the major contributions of this work is recognizing these three different objects: speed limit signs, the traffic lights, and the German highway specific signs which consist of highway route number signs along with the advance directional signs presented on the billboards of the German highway from the images captured with the camera mounted on the front of a vehicle.

The frames of the videos are sent to a pipeline which has a set of three algorithms each working for the recognition of different signs as mentioned above. The initial phase of each algorithm contains some pre-processing techniques such as color conversion, thresholding, grayscale conversion, and noise reduction. The YCbCr color space is used for the detection of the speed limit sign, and HSV color space for traffic light since they are less sensitive to illumination changes and give better results during the implementation.

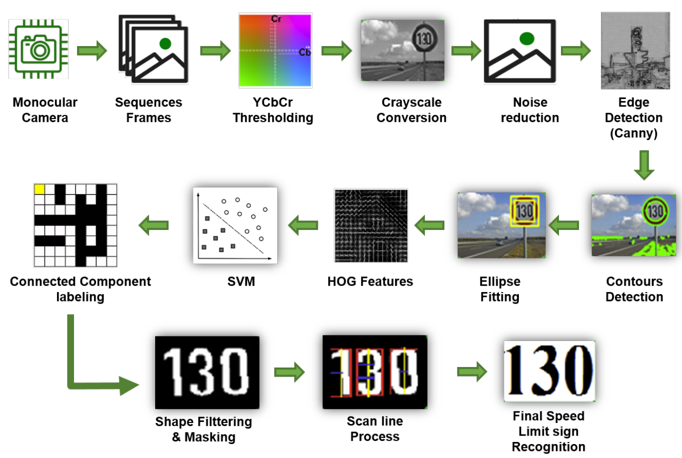


Fig. 3: Speed Limit Sign Detection

One of the algorithms is dedicated to the recognition of a speed limit sign which is based on contours. The contour-based detection gave better results with edge information. So, canny edge detection is used before finding contours. Finally, the ellipse fitting technique has been used to find the speed limit signs as shown in Fig. 3. This technique has successfully detected a range of limit signs including the misshaped ones which are warped from the regular round shapes. Even though a successful detection of signs had been generated, a significant quantity of false positives still existed. To reduce these, a linear SVM classifier is used which was trained using the HOG features. The BelgiumTS Dataset [16] had been used for this purpose. The recognition of the speed limit is done using the connected component labeling technique followed by some shape-based filtering and then the scan-line process. The technique can recognize any speed limit signs captured from the camera under suitable light conditions.

The second algorithm is used for the detection of traffic lights. The blob detection technique is used for this purpose. The input to this technique is a binary image which is a result of a sequence of pre-processing steps as shown in Fig. 4. In the color thresholding stage, three different ranges are used for extracting the red, green, and yellow color information. This led to the detection of the number of blobs (red, green, and yellow) present in the frames as a result of the blob detection technique. After that, contour properties and some shape adjustment techniques are used which could extract the traffic light box present in the frame that contains the detected blobs. Lastly, for the accurate detection and recognition of the traffic lights, three different SVM classifiers are used, one for each traffic color using the histogram of oriented features. As a result, the algorithm effectively recognized the traffic lights taken from the camera.

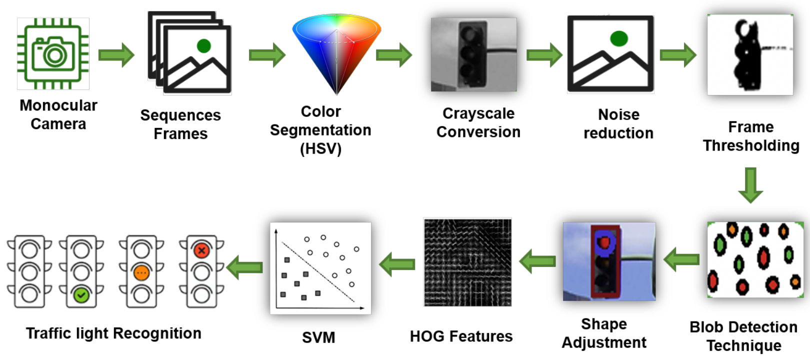


Fig. 4: Traffic Light Detection

The third and the final algorithm is used for the detection of the German highway route numbers present in the billboards of the German highway. Firstly, the image is grayscaled, and then the bilateral filter is used for the reduction of noise. After that, the Canny edge detector is used for extracting edge information. The results are improved by using a bilateral filter before using the edge detector, as contrary to previous detection methods, in which the Gaussian filter was used. The focus of this algorithm is to find the shapes inside the billboard signs. Therefore, a Region Of Interest (ROI) is created using the edge information and then finding the boundaries of the billboards using the contours. After the ROI is extracted, a shape-based filtration is applied using the contour properties yet again that could extract the relevant shapes that look similar to advance directional and the German highway route number signs as shown in Fig. 5. Now, the German highway route number and the advance directional signs are detected using the two separate procedures.

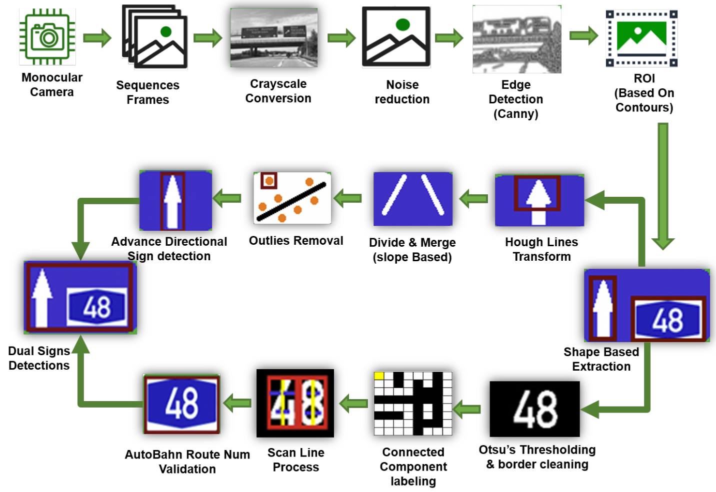


Fig. 5: German highway Specific Sign Detection

The advance directional sign is detected based on the presence of a pointed arrowhead. The relevant portion of the arrowhead sign is cropped and then the Hough transform is used to detect the lines. Left and right slanting lines are used to recognize the arrowheads. And for the detection of the German highway route number signs, the cropped region is cleaned at first using Otsu's thresholding and border segmentation. After that, connected component labeling is used followed by the scan-line process for the effective recognition of the digits present inside the sign. The route number sign is validated by the recognition of the digits inside the sign. The successful detection of both the German highway route number and the advance directional signs are strong candidates that are useful for classifying the German highway.

A weight-based classification system is proposed based on the recognition result of the three sub-systems. Traffic speed limit signs which are in the range of 80-150km/hr is provided with a weight of 0.35, whereas the absence of a traffic light in every 1500 frames is provided with a weight of 0.25, the most weight is provided to the German highway specific signs with 0.4. If one of thee subsystems generate a result within the classification boundaries, the German highway driving scenario is detected. Subsequent outputs from the sub-systems would increase the weight, thus increase the confidence of the classification. Along with the positive weights, a negative weight is also provided in the case when more than 1 traffic light is detected within every 1500 frames as the frequency of traffic lights in German highways are very low. The classification system is also showcased using Table 1.

Table 1: Design Criteria for Classifier System

<table>
<tr><th>Criteria</th><th>Features</th><th>Score</th><th rowspan="4">$0.8 \geq \sum(\text{Score}) \leq 1$
German Highway -> Yes</th><th>Features</th><th>Score</th><th rowspan="4">$\sum(\text{Score}) < 0.8$
German Highway-> No</th></tr>
<tr><td>Speed Sign</td><td>80-150</td><td>0.35</td><td>< 80</td><td>0.0</td></tr>
<tr><td>Traffic Light</td><td>Less frequent [Not Repeating within 1500 frames]</td><td>0.25</td><td>More frequent [Repeating within 1500 frames]</td><td>0.35</td></tr>
<tr><td>German Highway Specific Signs</td><td>Detected</td><td>0.4</td><td>Not Detected</td><td>0.0</td></tr>
</table>

5 Result & Evaluation

The evaluation of the results achieved was evaluated based on three criteria. These were the recognition accuracy of the three sub-systems, the computation time for each of the algorithms both individually and merged, and the correctness of the weighted confidence of the classifier. Implemented algorithms were tested in a total of 62,800 frames which were extracted from several videos for recognizing traffic speed signs and traffic lights and provide an average accuracy of approximately 99%.

(a) Speed Limit Sign (b) Traffic Light

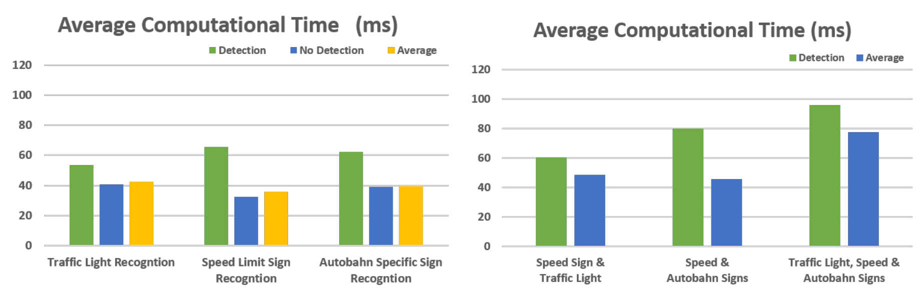
Fig. 6: Recognition of Speed Limit Sign and Traffic Light

The analysis showcased in Fig. 6a and Fig. 6b indicates that the algorithms detect the speed limit sign and traffic light as expected and the outcomes were drawn on the images. Similarly, the German highway detection algorithm was tested on several custom made videos with a total of 20,361 frames and generates a recognition rate of approximately 99%.

Due to the algorithms being developed and tested under the Raspberry Pi 3b+ models of "CE-Box", the computation was always a bottleneck of this research. Hence, two different evaluation were carried out. First, the algorithms were allowed to be run on different Raspberry Pis simultaneously. Later, all three

Fig. 7: The German Highway Specific Sign Recognition

algorithms were merged and ran under the same Raspberry Pi. The results showcased the difference in computation time for all the algorithms when it comes to detecting the object. It took almost twice the amount of time to compute the same object from the same video for the combined algorithm. Details can be seen in Fig. 8.



(a) Individual Algorithms (b) Combination of Algorithms

Fig. 8: Average Computational Time (in seconds)

With the generation of results from any of the three sub-systems, it is provided to the classifier. Depending on the generated result, the classifier provides a confidence weight based on which the German highway driving scenarios are classified. The confidence weight will keep on increasing as long as any of the sub-systems generate information that falls within the classification criteria. If the sub-systems do not generate any result or generate a result that is out of bounds of the classifier, the confidence keeps on losing weight until German highway driving scenarios are not classified anymore. The German highway route numbers and the directional signs are detected as expected and the output is indicated on the image and also the result of the classifier can be seen in Fig.

7. A statistical overview regarding the Precision, Recall, and Accuracy of the algorithms is shown in Table 2.

Table 2: Results & Evaluation of Algorithms

Algorithms	Number of Frames	Average True Positives	Average False Positives	Average False Negatives	Average True Negatives	Average Precision	Average Recall	Average Accuracy
Speed Sign	29238	27	0.133	1.4	1920.67	0.99	0.949	0.999
Traffic Light	33562	247.467	2.533	6.067	1981.4	0.941	0.967	0.996
German Highway Specific Signs	20361	20.4	0.4	2.333	1334.27	0.878	0.982	0.998
Merged Algorithms	20790	98.289	1.022	3.267	1745.44	0.936	0.966	0.998

6 Conclusions & Future Aspects

In this paper, three algorithms were developed to recognize the speed limit sign, the traffic light, and the highway traffic sign. Our solution is evaluated using the German Traffic Sign Recognition Benchmark [17]. The proposed solution is implemented using computer vision and machine learning approaches to achieve a high perception level for situation awareness. As these objects are recognized, the driving mode will be classified as a high driving mode or city driving mode. For testing and evaluating the system, a custom hardware unit called "CE-Box" was used, which consisted of Raspberry Pi 3b+ models. The research demonstrated that the newly proposed classification mechanism is capable of classifying German highway driving scenarios with respect to some aspects and that it is also scalable for other applications and perception systems. Although the presented work concentrate on the German Highway Driving Scenario. It can be customized and generalized by considering the rule and regulations from other countries as well.

Inspite of the number of sub-systems used in the proposed classification system generated results with high accuracy and robust performance, the confidence weights of the classification system itself could be improved a lot by adding more sub-systems to it. German highway entrance and exit traffic signs were not considered for this research project. Including more traffic signs could also be beneficial. Classification of other driving traffic modes can also be implemented and evaluated with the proposed work. Hardware used in the "CE-Box" can also be updated and evaluated for better performance feedback improving the computation time of the algorithms.

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