DETECTION OF SELECTED REGULATORY TRAFFIC SIGNS USING COMMON DASHBOARD CAMERA

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Resume

Nowadays, many modern vehicles contain a lot of systems for autonomous functions or driver assistance systems (traffic sign recognition). Modern vehicles contain many embedded systems and control units (also for signal and image processing), so implementation of deep learning or AI-based algorithms is possible. In older vehicles, mentioned systems missing or they are limited. In this paper is presented a design of algorithm for detection of selected regulatory traffic signs to extend the selected autonomous or intelligent functions of older vehicles. Algorithm is based on shape and color detection of key features of selected regulatory traffic signs (amplification of specified color pixels and Generalized Hough Transformation). This algorithm can be easily implemented or used in many other applications, such as for driving mobile or robotic platforms. Detection efficiency of algorithm is also evaluated in this paper.

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1 Introduction

Traffic sign recognition is an important part of autonomous driving, advanced driver-assistance systems (ADAS), and smart transportation systems. Traffic signs are important to ensure safe driving and efficient traffic flow. With the development of car assistance systems, the requirements for automated traffic sign detection are also increasing [1]. Traffic sign detection is often realized based on images taken from the dashboard cameras. Compared to other items like automobiles and trees, traffic signs are often smaller in images [2]. Usually, they take up less than 5% of the entire image. Extracting the necessary elements from photos of traffic signs is quite difficult because of their small size.

There are several methods used for traffic sign recognition, often involving machine learning, deep learning, and computer vision techniques. One of the most used computer vision techniques is color-based segmentation. Color-based segmentation is a fundamental technique in traffic sign recognition that uses distinctive colors (e.g., red, blue, yellow) of traffic signs to detect and classify them effectively. This technique uses only color information. As mentioned in [3], Gaussian distributions are used to model each color for detection. Another technique used is color space extraction from various color models, e.g., HSL (Hue, Saturation, Value) [4-5], and consecutive creation of binary images that isolate objects of specific colors. The HSL color space is most effective for this purpose [6].

Segmentation techniques, based on the shape detection, are very useful for searching circular, triangular, or rectangular shapes [7]. These algorithms often use the Hough Transform, which can identify traffic signs based on their geometric shapes.

Hybrid methods combine traditional computer vision and deep learning techniques for improved recognition. These methods are used to speed up the detection of objects through preprocessing procedures. While the deep learning approaches handle classification, methods such as color segmentation or the Histogram of Oriented Gradients (HOG) technique reduce the number of searched features [8].

Presented algorithm is developed mainly for older vehicles to create basic or extend intelligent or autonomous functions. Detection of selected traffic signs is important, especially in the cities where the traffic infrastructure is very complex and can negatively affect the driver's attention. In this paper is given an approach to the speed limit traffic signs, but the algorithm can be easily extended for other shapes and colors of traffic signs. The algorithm is divided into two steps: detection of traffic sign and reading the textual information from speed limiting sign. Information about speed limit can be used like a single information for driver (e.g., information on head-up display) or serve as input for adaptive cruise control.

2 Materials, methods, algorithms

The main goal of the proposed algorithm was to create a non-expensive and computationally simple system for detecting regulatory traffic signs (especially speed limits) using a car dashboard camera. Common dashboard cameras store video data using codecs (e.g., H.264). Reducing the memory storage demands usually results in worse image quality and color fidelity, or strong block effects [9]. Lower image quality is always a big challenge for vision algorithms focused on object detection in images.

On the other side, for the detection of specific regulatory traffic signs (speed limits), several typical features are assumed, which facilitate the detection process: selected regulatory signs have regular shape and expressive color to be in contrast with surroundings (typically circle with red rim, triangle with red rim…). From this point of view, one can focus on partial algorithms that search for or amplify image regions with specific colors or search for regular shapes.

In this work, several variants of possible algorithms are used and compared and selected the most effective and successful one. The algorithms were primarily tested offline on selected video sequences and static images from a real dashboard camera (MiVue C570). For the evaluation of algorithm efficiency, the standard metrics based on computing precision and recall, was used.

First detection was based on Pattern Matching or Geometric Matching algorithm [10-13] running on an 8-bit grayscale version of the camera image. This pilot experiment was inspired by work [5]. In this study, the mentioned detection techniques were used for ideal (synthetic) images of traffic signs, except those with textual information (e.g., speed limits). We updated this work with this kind of traffic sign and real input images obtained from a dashboard camera. Pattern Matching is based on normalized cross-correlation between the inspected image and the defined template. Due to possible color variations of traffic signs, depending on weather conditions (rainy, sunny, misty, dark), only the intensity character of detected objects is assumed and classic Pattern Matching is preferred over the Color Pattern Matching. Assuming the geometrical features of traffic signs, we used Geometric Matching [10-13], also running on an 8-bit grayscale image from a camera.

Unfortunately, a real complex scene from a dashboard camera (containing buildings, trees, other traffic infrastructure, image noises and distortions) produces many image gradients (many false edges), which can be counterproductive using e.g., Geometric Matching. The accuracy or recall metrics reached approximately 20-30% in most cases. From this point of view, another version of the algorithm was proposed.

2.1 Algorithm - part 1: detection of traffic signs in input image

In our proposed final variant of the algorithm, we combined the color detection (represented by amplifying the given color channel) and shape detection provided by Generalized Hough Transformation (GHT) [14-15] for searching regular shapes (ellipses), followed by

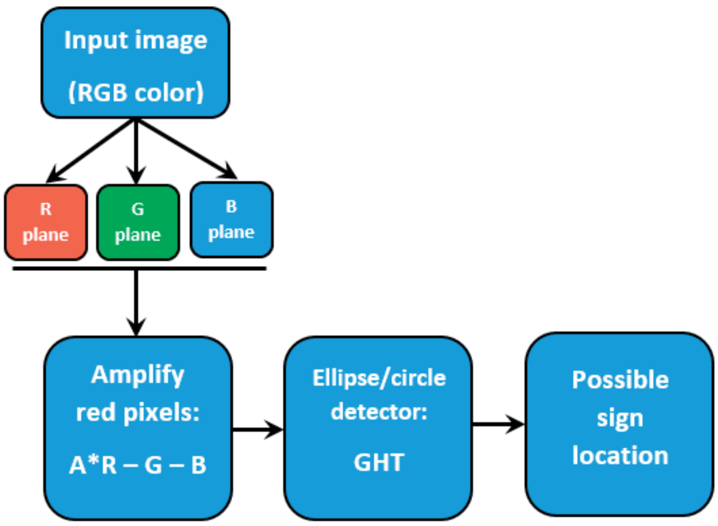


Figure 1 *Detecting the traffic sign in entire dashboard image - block diagram*

reading the textual content by an OCR algorithm. This pilot research was focused on circular signs with a red rim. Generalized Hough Transformations allow for the detection of other shapes: triangles, squares, hexagons. The first part of the detection algorithm is shown in Figure 1.

When using the NI LabVIEW environment for developing and debugging the algorithm, the Generalized Hough Transformation is built in a function called Shape Detection. The shape was set to an ellipse just from a practical point of view: the traffic sign in a real dashboard camera image is often an ellipse due to the strong variability of projection (when a car passes the traffic sign in a road bend, the circle changes to an ellipse). The detailed overview of the Shape Detection function is given in [11]. Using this function, users can modify several parameters for shape detection and its acceleration (searching for edges/gradients in the image and filtering of edges based on strength and length, setting the range for minor and major radius of the ellipse, setting the match score for the ellipse).

To simplify the input for the Shape Detection function, a preprocessed version was created of the input color image and amplified the red pixels (when detecting the signs with red rims). The resulting monochromatic image I_r after the red amplification, is given by the formula:

$$I_r = A * R - G - B, \tag{1}$$

where A is the amplification constant for the red channel R, G is the green channel, and B is the blue channel of the input color image. Constant A is set empirically to 1.5 - 2.5. For further enhancement of the proposed algorithm, this constant can be computed based on the global mean value of the input image. The mean value of the input image strongly corresponds with weather conditions and illumination of the scene. The resulting amplified image I_r is set to 8-bit resolution using the saturation method.

Figure 2 shows the detection of a circular traffic sign in the input dashboard camera image.

In many cases, the traffic sign is detected twice (inner and outer edge of red rim), duplicities are removed by a simple algorithm using comparison of detected center points. Immediately after this step, the bounding boxes (Figure 3) are computed, and detected signs are extracted from the original input images. If the traffic sign detection is done upon the inner edge, the given ellipse major radius is increased by 10%, for

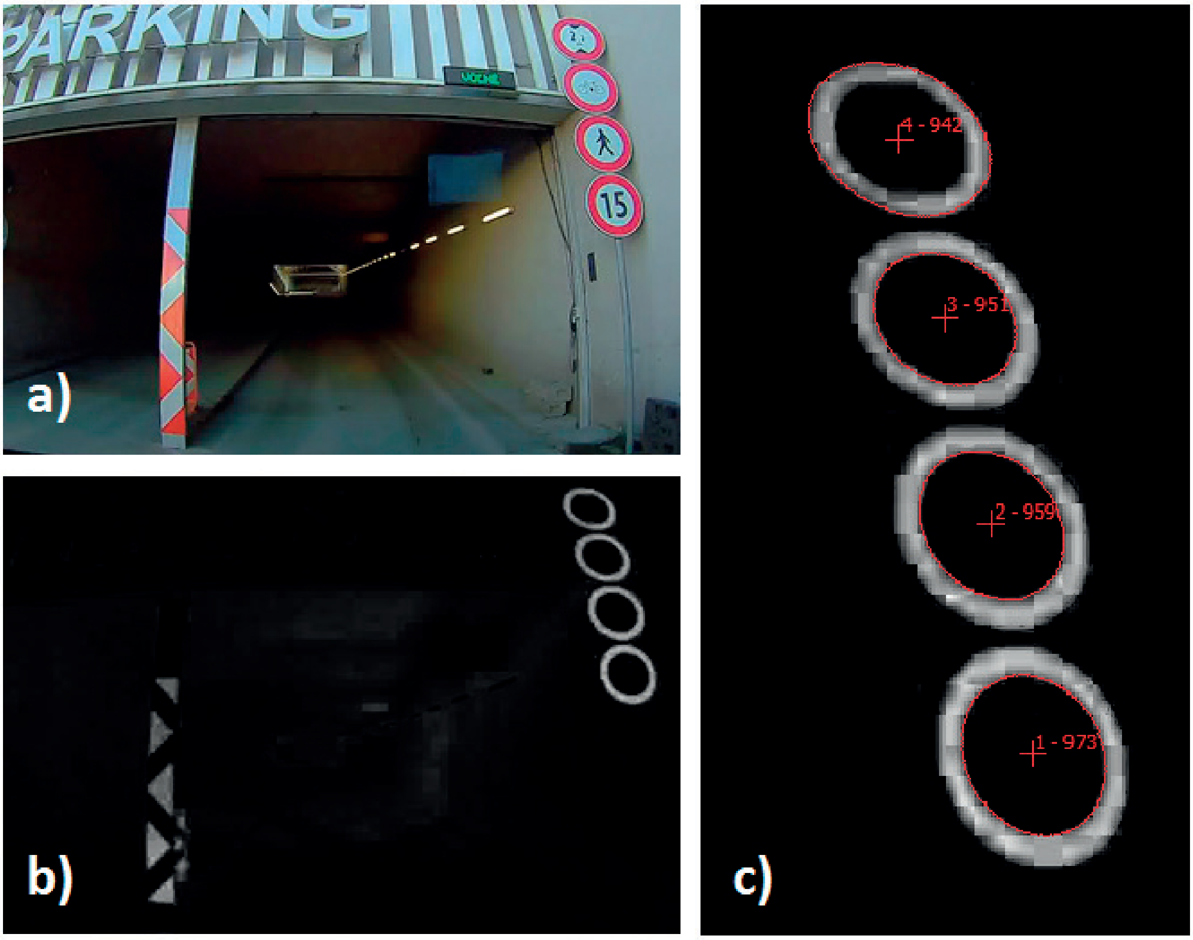


Figure 2 *Detection of ellipses in input image: original color image (a); monochromatic image* I_r *after amplification of red pixels (b); output from Shape Detection function with highlighted center, radius and matching score (c)*

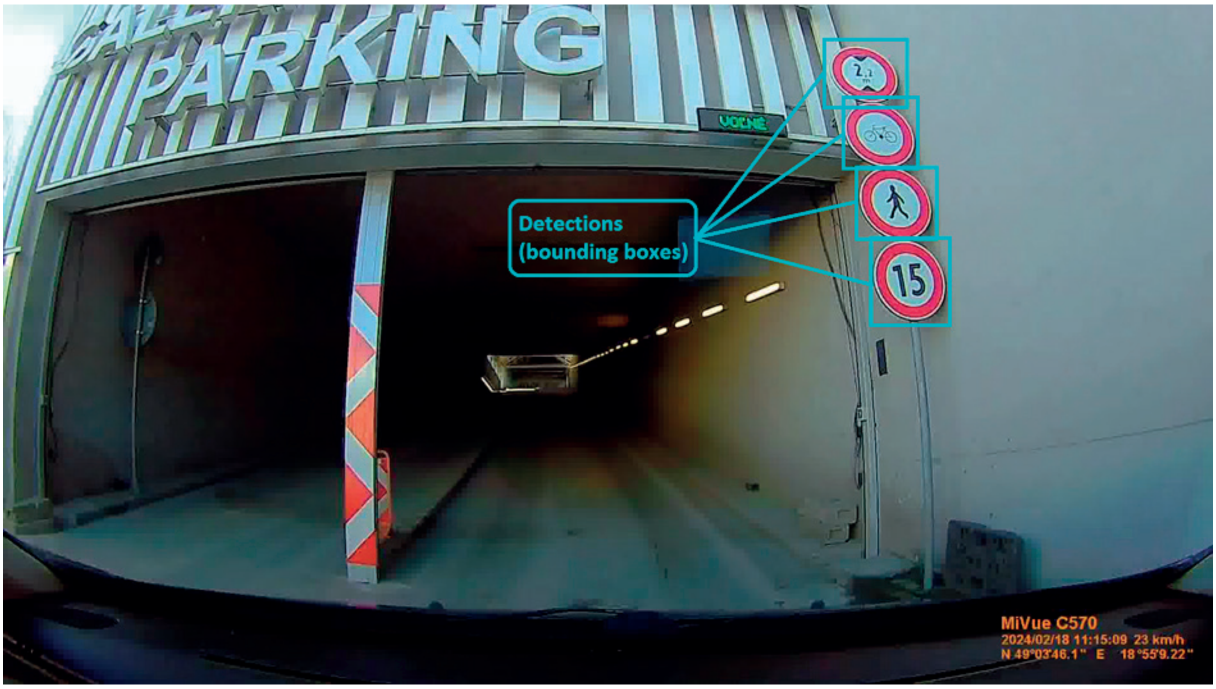


Figure 3 *Construction of bounding boxes to detected circular traffic signs*

example. This ensures that the traffic sign is extracted completely from the original image. Extracted image regions are then sent to the OCR algorithm for reading textual information about the speed limit.

2.2 Algorithm - part 2: preparation to OCR

The optical character recognition is a process that converts an image of text into a machine-readable text. The OCR is not a universal algorithm, but the main engine of this process is based on the classification of image patterns into classes representing numbers or characters. In work [16] one can see that classification of image patterns can be provided by conventional methods of classification (e.g., k-Nearest Neighbor algorithm) or by using neural networks. In our implementation, the OCR algorithm was based on the k-Nearest Neighbor algorithm. In this approach, each image pattern, representing an alphanumerical character is binarized, then described by selected features (the feature vector is created). In the last step, the selected distance (Manhattan, Euclidean…) of the current feature vector is computed from each feature vector in the training set. From k minimal distances, the classification class is selected by the majority affiliation to the trained class.

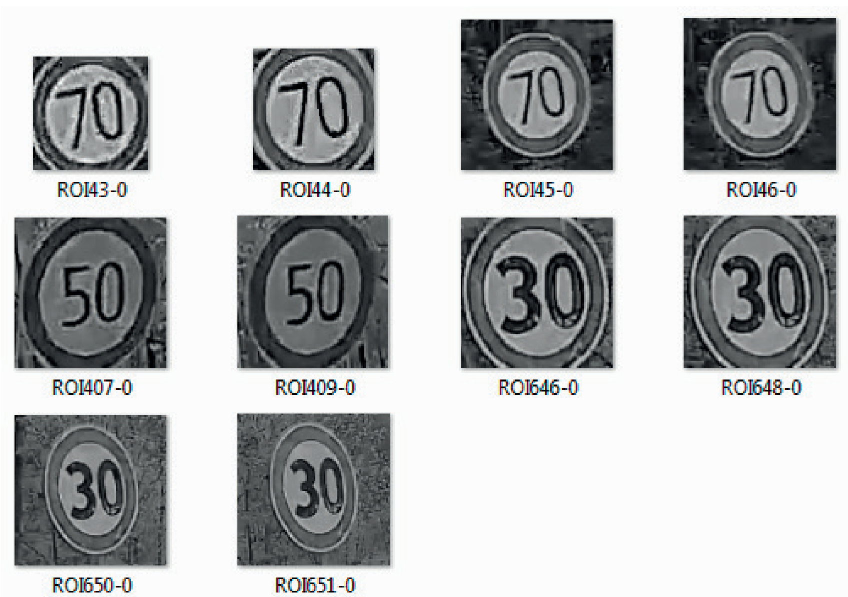


Figure 4 *Several samples in OCR training dataset*

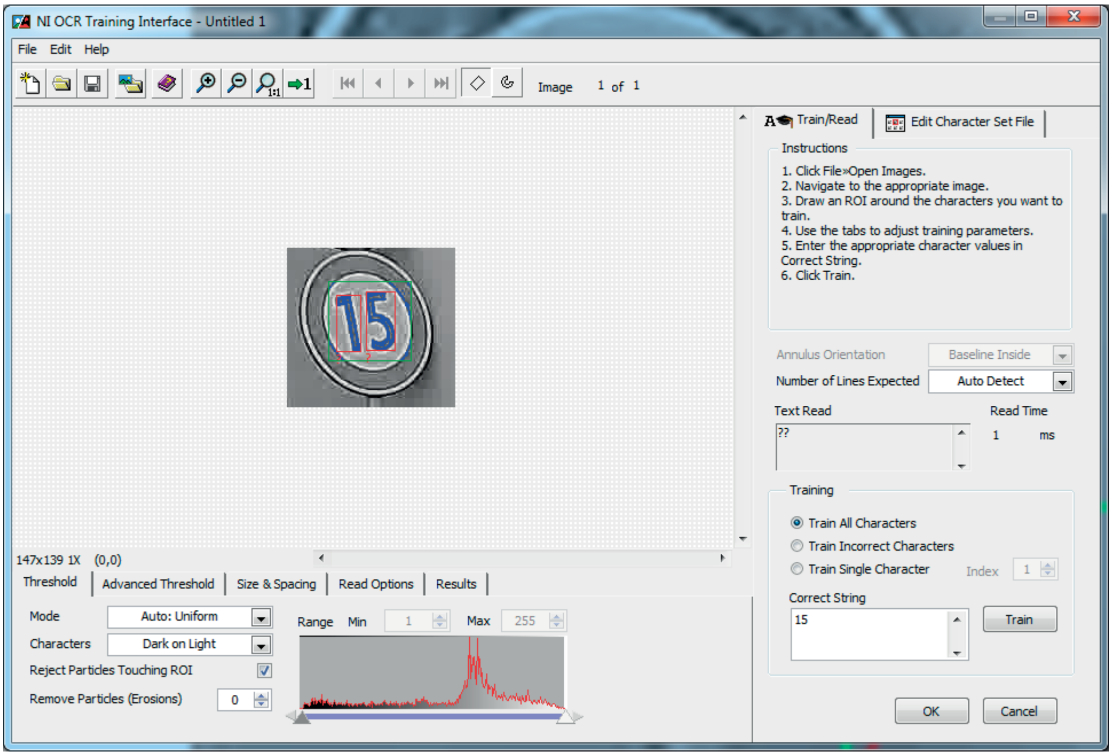


***Figure 5** NI OCR Training interface*

Based on [11], the features of binarized image patterns, representing text elements, must be scale and rotation-invariant: circularity, elongation, convexity, analysis of holes, spread, and slenderness.

The first part of the classification process is building the training dataset. When focusing on speed limit traffic signs, we created a dataset from numerical symbols only. In our dataset, each symbol, from 0 to 9, was used in at least 50 samples. Several samples of OCR training datasets are shown in Figure 4. The dataset was created by combining the extracted traffic signs from the dashboard camera using a previously described algorithm, or using images taken from Google Street View. All the outliers (damaged signs, distorted signs) were removed from the training process.

After the training dataset was collected, the training process of OCR was provided in LabVIEW using the function NI OCR Training Interface (Figure 5).

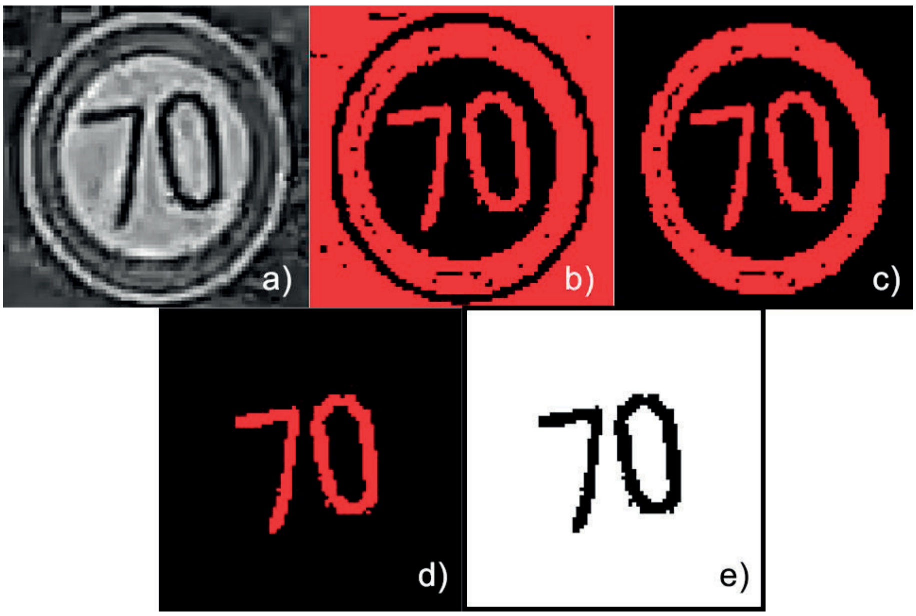


***Figure 6** Morphological cleaning of extracted traffic sign before OCR: original of extracted traffic sign in 8-bit intensity mode (a); thresholding by Entropy method (b); removing border objects (c); filtering the objects lying outside of defined surroundings of image center point (d); binarized characters in black and white scale - dark objects on bright background (e)*

2.3 Algorithm - part 3: Classification by OCR

To increase the efficiency of the classification process of a trained OCR system, a morphological clean-up algorithm was proposed. The OCR running directly on extracted traffic signs from the original image, and converted to an 8-bit intensity image, had worse results than OCR running on images after the morphological cleaning (Figure 6). The morphological algorithm consists of:

- binarization (Automatic threshold, Entropy method [11]);
- removing objects touching the image edge;
- keeping objects with center of mass lying in the given surroundings from the image center.

After this morphological cleaning, the OCR focuses mainly on proper binary patterns representing numerical symbols.

In this algorithm, other types of circular traffic signs with red rim can be detected and extracted from the input image (see Figure 2 or Figure 3). If any other symbol except numerical one appears in the sign content, the OCR function returns symbol "?" and this sign is ignored. If there is a requirement for classification of other types of traffic signs, NI Vision Particle Classification Training module serves as extension of OCR for any binary symbol.

3 Experimental results

To verify the efficiency and accuracy of the proposed algorithm, 10 video sequences were selected. From each video sequence, we extracted 100-200 frames where the traffic signs - selected speed limits - had a critical radius (at least 30 pixels for minor or major radius). Video sequences were captured by the dashboard camera MI Vue C570 using the built-in codec H.264 (MP4 container). Different illumination and scene conditions were contained in video sequences (sunny, night, rain, traffic signs in shadow, traffic signs in front of buildings, trees, etc.). The entire algorithm was implemented into the NI LabVIEW interface (and later tested during driving - Figure 7). To amplify red pixels, we used a gain constant A = 1.75.

The detection performance of the entire process is evaluated in two steps. First, we measured the precision and recall for the detection of circular traffic signs (speed limit) from the input image. The accuracy of the OCR process was measured separately.

For evaluation of the traffic sign detection (the first step), the entire set of input images (a total of 1395 images) was manually annotated. True positive (TP), false positive (FP), and false negative (FN) states used for the computation of performance metrics are illustrated in Table 1.

The standard formulas for precision (P) and recall (R) computation were used:

$$P = \frac{TP}{TP + FP} \cdot 100\%, \tag{2}$$

$$R = \frac{TP}{TP + FN} \cdot 100\%. \tag{3}$$

Precision parameter expresses how many signs were detected in proper locations in images (the influence of false detections). Recall expresses how many signs were detected from the real number of traffic signs. In Table 2 one can see the precisions and

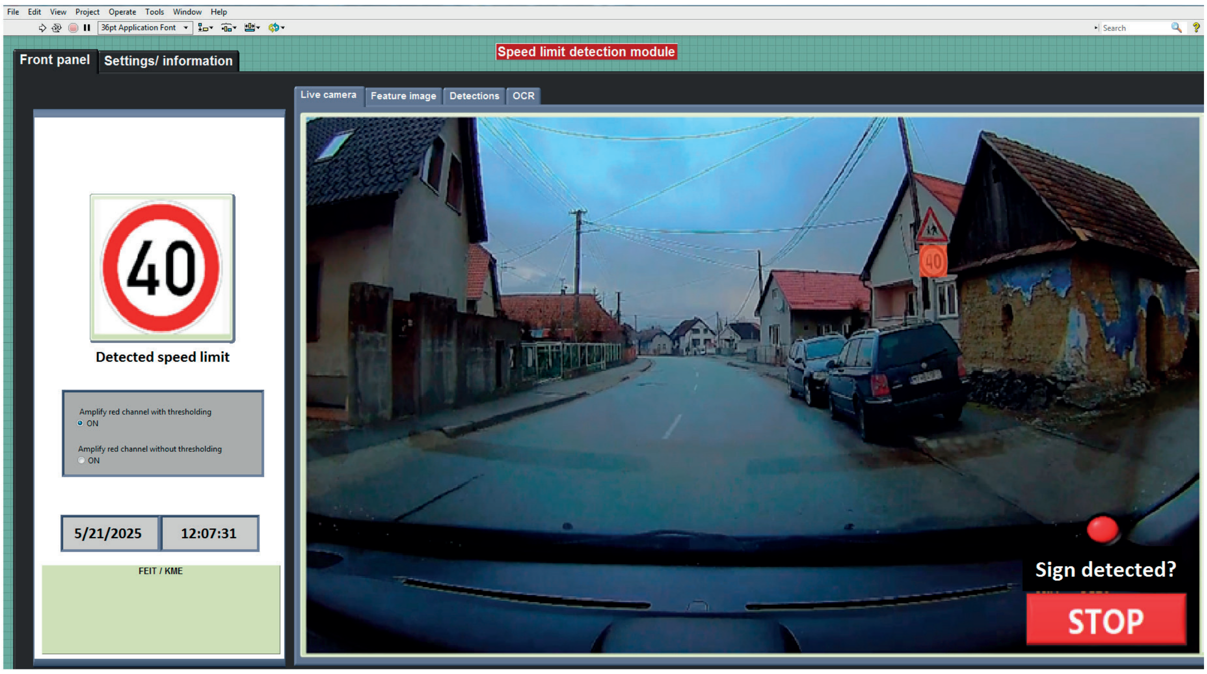


Figure 7 *Algorithm implemented into LabVIEW and tested during car driving*

recalls for each video sequence.

To measure the efficiency of the OCR algorithm, a set of images (real traffic signs contents) was prepared with almost 500 characters. Number of each character, from 0 to 9, is shown in Table 3 along with success rate of correct reading in OCR.

Table 1 *TP, FP and FN states in traffic sign detection*

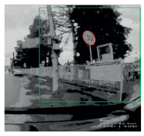
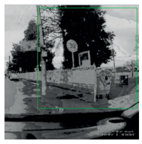
States	Sign detection	Images
True positive (TP)	Sign detected properly	
False positive (FP)	Sign detected in wrong location	
False negative (FN)	Sign not detected	

Table 2 *Evaluation of precision and recall for speed limit sign detection*

Sequence #	Weather / conditions	Precision [%]	Recall [%]
1	Sunny, field	95.37	92.66
2	Sunny, city	91.67	89.37
3	Sunny, combined backgrounds	96.74	91.67
4	Sunny, sun directly into the camera	25.14	24.35
5	Cloudy, city	89.37	87.36
6	Sunny, city - shadows	88.73	87.98
7	Rain, city	79.67	71.42
8	Rain, field	85.67	80.35
9	Night, car reflectors	80.29	63.19
10	Night, street lighting	73.98	45.78

Table 3 *Evaluation of OCR conversion process*

Single character			
Character	Number of characters	Correctly read	Success rate
0	89	76	85.39%
1	43	39	90.69%
2	50	41	82%
3	56	48	85.71%
4	45	35	77.77%
5	33	28	84.84%
6	42	37	88.10%
7	40	36	90%
8	45	38	84.44%
9	33	18	75%

All characters		
Number of characters	Correctly read	Success rate
476	396	83.19%

4 Discussion and conclusion

In this paper is presented an algorithm for detection and reading of selected regulatory traffic signs (especially speed limit signs, circular with red rim and textual-numerical content). Algorithm is based on traditional methods for color and shape detection following by OCR based on kNN classification of binarized numerical characters.

As one can see, the detection power of algorithm must be evaluated in two steps: accuracy of traffic sign localization from input image and accuracy of OCR reading process. The accuracy of localization and extraction of traffic sign from entire input image varies depending on the weather (scene illumination) conditions. The best results are achieved generally during the day, except in situations where the sun directly shines into the camera. The worse results were obtained during the rain and night. Success rate of OCR process varies from 75% to almost 91%. The most affecting reason for the process accuracy decreasing is usage of dashboard camera with serious image quality degradation and extreme weather conditions. In the future, many values set empirically, could be computed adaptively (e.g., the red channel amplifying constant A could be computed from global image illumination characteristics).

On the other side, precisions and recalls in Table 2 are computed from a set of independent images and they seem not to be so high. During the real driving, however, a particular road sign is in the camera field for several seconds. The detection system often obtains several dozen images from it. In this case, for example, 80% recall is sufficient to confirm that a particular sign is correctly detected. Providing such experiments, the “global” recall can reach 95-100%.

Due to relatively simple partial algorithms, this solution can be easily implemented into older vehicles to extend intelligent or autonomous functions. Any other types of traffic signs can be easily added by the same process (reading other colors and shapes, training general binary patterns for traffic sign contents).

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Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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