

# Detecting, Tracking and Recognizing License Plates

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**Abstract.** This paper introduces a novel real-time framework which enables detection, tracking and recognition of license plates from video sequences. An efficient algorithm based on analysis of Maximally Stable Extremal Region (MSER) detection results allows localization of international license plates in single images without the need of any learning scheme. After a one-time detection of a plate it is robustly tracked through the sequence by applying a modified version of the MSER tracking framework which provides accurate localization results and additionally segmentations of the individual characters. Therefore, tracking and character segmentation is handled simultaneously. Finally, support vector machines are used to recognize the characters on the plate. An experimental evaluation shows the high accuracy and efficiency of the detection and tracking algorithm. Furthermore, promising results on a challenging test set are presented and the significant improvement of the recognition rate due to the robust tracking scheme is proved.

## 1 Introduction

There is a need for intelligent traffic management systems in order to cope with constantly increasing traffic on today's roads. Video based traffic surveillance is one of the key parts of such installations. Beside detection and tracking of vehicles, identification by license plate recognition is important for a variety of applications like access-control, security or traffic monitoring.

Generally, license plate recognition systems consist of two separate parts. First, license plates are detected within a single frame of a traffic video sequence and then character recognition is applied to identify the characters on the plate. Several methods have been proposed for the detection of license plates. For example, [1] use a mixture of edge detection and vertical pixel projection for detection module. In the work of Jia et al. [2] color images were segmented by the Mean Shift algorithm into candidate regions and subsequently classified as plate or not. The AdaBoost algorithm was used by Dlagnekov and [3] for license plate detection on rather low resolution video frames. Zimmermann [4] proposed a different approach for the localization of license plates. Instead of using properties of the plate directly, the algorithm

I. Donoser, C. Arth, and H. Bischof

Several approaches for recognizing the characters on the plate after sub-region detection were proposed. Shapiro et al. [1] use adaptive iterative threshold analysis of connected components for segmentation. The classification is then performed with two sets of templates. Rahman et al. [5] used horizontal and vertical intensity projection for segmentation and template matching for classification. Dlagnekov and Belongie [3] use the normalized cross correlation for classification by analyzing the whole plate, hence skipping segmentation.

Although much scientific work has focused on recognizing license plates from video sequences, surprisingly little work has been done on integrating a tracking scheme to gather additional representations of the plate for improving recognition rate. Furthermore, in the few systems that apply a tracking scheme, only simple and unstable approaches are used, as e. g. by Dlagnekov and Belongie [3] who perform tracking by simply repeating detection for building correspondences.

The main contribution of this paper is a novel framework which unifies detection, tracking and recognition of license plates in a robust and efficient way. The guiding idea is to base detection, tracking and character segmentation on the same principles which allows to provide segmentations of the individual characters for recognition in addition to accurate and robust license plate localization in subsequent frames. The framework is presented in detail in Section 2. The experimental evaluation is shown in Section 3.

## License Plate Recognition Framework

This section describes the entire framework for detection, tracking and recognition of license plates from traffic video sequences. The introduced system detects appearing license plates from the sequence by a novel algorithm which is based on the analysis of Maximally Stable Extremal Region (MSER) [6] detections. The concept, introduced in Section 2.1, does not require any learning and is capable of detecting different types of international plates. After detection of a plate it is robustly tracked through the sequence by a modified version of the MSER tracking framework [7] as shown in Section 2.2. Therefore, for each appearing car in the video sequence a set of license plate representations is collected which is used to improve the subsequent character recognition. Section 2.3 describes how support vector machines are used to recognize characters on the different representations of each plate and how the results are combined by a voting scheme to achieve the final recognition result.

### License Plate Detection

The first step of every license plate recognition system is the detection of the license plates within a single frame of the traffic video sequence. We propose a novel detection scheme which is motivated by the work of Matas et al. [6]

ne does not require any learning scheme and is able to detect different international license plates without adaption.

etection algorithm is based on analyzing the results of a Maximally Extremal Region (MSER) detection [8]. MSERs denote a set of distinct regions and have proven to be one of the best interest point detectors for stereo vision [9]. All of these regions are defined by an extremal property of the intensity function in the region and on its outer boundary. Special MSERs form their superior performance as stable local detector. The set of MSERs is closed under continuous geometric transformations and is invariant to intensity changes. Furthermore, MSERs are detected in every scale. We mainly exploit these properties for segmentation purposes.

In general, two variants of MSER detection can be distinguished denoted as MSER+ and MSER-. While MSER+ detects bright regions with darker boundaries, MSER- finds dark regions with brighter boundary. Figure 1(a) shows an input frame from a traffic video sequence and Figure 1(b) and Figure 1(c) illustrate the corresponding MSER detection results as binary images. As can be seen, the license plate itself is identified as MSER+, whereas the characters on the plate are detected as MSER-.



MSER detection results can be used for detecting license plates in video sequences. MSER+ finds the license plate, whereas MSER- identifies the individual characters.

The underlying idea of our novel license plate detection scheme is to analyze the MSER+ and MSER- detection results. We are looking for a larger MSER+ region (license plate) that contains a set of smaller MSER- regions (characters). This combination is considered as license plate detection result. Furthermore, the detection is verified by checking if the MSER- regions are approximately aligned, if their center points approximately lie on a line and if the height of the MSER+ is in the range of the average MSER- height. After verification, the MSER+ is returned as license plate localization result and additionally segmented. The characters are provided by the corresponding MSER- detections. Although the detection process is simple, it is effective and allows stable and accurate detection of license plates in complex scenes. An exemplary result is



(a) Proposed algorithm



(b) AdaBoost result

license plate detection results. Figure (a) shows the single detection of the proposed algorithm indicated by the white border. 914 MSERs are detected, but only 14 regions fulfill the described criterion. Figure (b) shows the wrong and multiple detections of an AdaBoost algorithm.

For comparison, Figure 2(b) shows the result of an AdaBoost detector based on Haar-like features [10]. As can be seen the boosting framework returns multiple detections which need to be significantly post-processed, as e.g. by NMS (non-maximum suppression) to remove multiple detections. Our result is also more accurate as the bounding box provided by the boosting variant. Furthermore, training of an AdaBoost based classifier is a rather complex procedure, in this case was especially trained on Austrian license plates. Our approach does not require any learning scheme and is able to identify different types of international plates, because the simple criterion is fulfilled for almost all of them. Figure 3 shows detection results for different international types.



(a) Input image



(b) Characters (MSER-)



(c) Plates (MSER+)

Figure 3 shows detection results on international license plates where (b) shows the segmented characters detected as MSER- and (c) the plate detected as MSER+. As can be seen the

## Tracking of License Plates

detection of a newly appearing car in the traffic video sequence by its  
 ate, a robust tracker is applied to increase the number of character  
 ations for the subsequent recognition step. In general, any tracker can  
 but we propose to apply a modified version of the MSER tracking  
 k introduced by Donoser and Bischof [7] which has some advantages  
 st to other tracking schemes. First, it is efficient and stable and can be  
 o our specific requirements. Second, it provides an accurate segmenta-  
 e license plate and third, in addition to the tracked plate it also returns  
 tions of the individual characters on the plate (MSERs), thus tracking  
 entation are handled simultaneously.

MSER tracking framework was designed to improve the stability and  
 MSER detection results in video sequences. The tracker has to be initial-  
 assing the region to be tracked  $R_t$  detected in image  $I_t$  of the sequence  
 ework. The first step of the algorithm is to propagate the center point  
 ion  $R_t$  to the next image  $I_{t+1}$  and to crop a region-of-interest (ROI)  
 from the image. Then a data-structure named component tree [11] is  
 this ROI. Every node of the component tree contains one candidate  
 $_{t+1}$  for the tracking and the algorithms looks for the node which is most  
 to the region  $R_t$ . The best fit is identified by comparing feature vectors  
 ould for each of the nodes of the component tree  $C_{t+1}^i$  and the input  
 $R_t$ . The candidate  $C_{t+1}^i$  with the lowest Euclidean distance between its  
 vector and the one of the region  $R_t$  is taken as tracked representation.  
 ures calculated are mean gray value, region size, center of mass, width  
 t of the bounding box and stability. All of these features are computed  
 ally [12] during creation of the component tree. Thus, no additional  
 ion time is required. After detection of the new representation the de-  
 eps can be repeated for tracking the region through the entire sequence.  
 iginal MSER tracking framework was designed for tracking arbitrarily  
 ion, but we adapt the method to our specific requirements of track-  
 e plates. In our framework, the MSER tracking algorithm is initialized  
 ult of the license plate detection algorithm presented in Section 2.1.  
 ve focus on license plates we reformulate the feature comparison ap-  
 y replacing the Euclidean distance computation by a simpler, but more  
 equation based on comparison of two distinct features, the size and the  
 arity of the region. Thus, in our framework the tracked representation  
 y calculating a distance value  $\Delta(R_t, C_{t+1}^i)$  for every candidate region

$$\Delta(R_t, C_{t+1}^i) = \frac{abs(|R_t| - |C_{t+1}^i|)}{|R_t|} + (1 - \vartheta(C_{t+1}^i)), \quad (1)$$

$|R|$  denotes the size of the region and  $\vartheta(\dots)$  is the rectangularity. Then,  
 date  $C_{t+1}^i$  with the lowest  $\Delta(R_t, C_{t+1}^i)$  value is taken as final repre-



Figure 4: Illustration of license plate tracking. The images show a traffic scene and the detected license plate. The characters on the license plate are highlighted in white.

through the sequence and the detected MSER- regions within the license plate are provided as segmentations of the individual characters. Furthermore, the tracking scheme is also used for discarding false positives of the tracking step by removing non-moving or unstable plate tracks.

Figure 4 shows two frames of a traffic video sequence, where accurate license plate segmentations are provided in addition to the segmentation of the eight characters of the plate.

## Character Recognition

The next step of our framework is to recognize the individual characters on the license plates based on support vector machines (SVMs). SVMs were first introduced by Vapnik [13] and have proven to be an efficient tool for classification in optical character recognition (OCR) of handwritten digits or license plate characters [14]. For an introduction to SVMs and other kernel methods see for example [15].

Generally, SVMs are designed for binary classification problems. Because license plate character recognition is a multi-class problem we apply a method based on a combination of several binary SVMs. The strategy is called *one-vs-one* where for every pair of output classes an individual SVM is trained, resulting in a total of  $n \cdot (n - 1)/2$  classifiers. Then all classifiers are evaluated, the votes are summed up and the class with the maximum number is chosen.

Since the provided character segmentations are aligned, and then the *one-vs-one* approach is used to classify each character independently of all the others. The presented tracking approach provides several license plate representations for every car and therefore, we also have several classification results for every character on the plate. A majority voting scheme is then used to determine the final character recognition result for every car.

Figure 5 shows a sequence of tracked license plates, the segmented characters and the corresponding classification results. As can be seen, the single image classification provides wrong assignments, but the subsequent majority voting

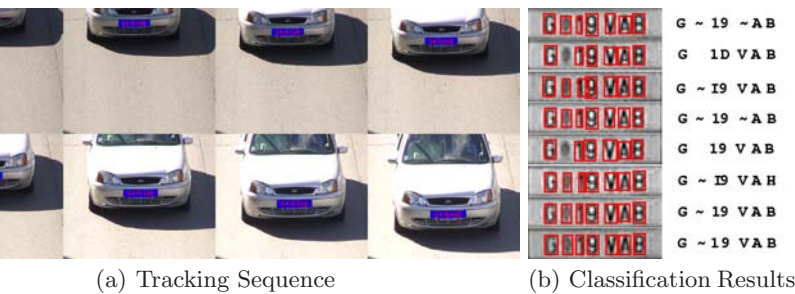


Figure 5. Recognition is improved by using several license plate representations provided by the proposed tracking scheme. The final result based on a majority voting for this plate is G~19VAB which matches with the real plate number.

Figure 6 shows how to combine a sequence of single image based recognition results to obtain the final classification.

### Framework

The proposed framework is able to analyze traffic video sequences in real-time. It detects appearing cars by localization of their license plate. After a one-time detection, the plate is robustly tracked and several representations of the license plate are collected. Until tracking fails the available repeated segmentations of the license plate character on the plate are used to improve the recognition rate along the tracking sequence and to determine a final result by the majority voting scheme. The running times of the individual steps of the concept for analysis of a license plate sequence of size  $352 \times 288$  are shown in Table 1.

Table 1. Running time per image of the individual steps of the framework for analyzing a license plate sequence of size  $352 \times 288$

	Detection	Tracking	Recognition
Running time	70ms	5ms	6ms

### Experimental Evaluation

We evaluated our framework on a challenging traffic video sequence in the type of Figure 5(a) which was filmed from a footbridge. The provided resolution was  $352 \times 288$  and therefore the characters on the plate only have an average size of 10 pixels in the sequence.

I. Donoser, C. Arth, and H. Bischof

on the challenging data set and shows how the recognition rate is significantly improved by using several plate representations provided by the tracking

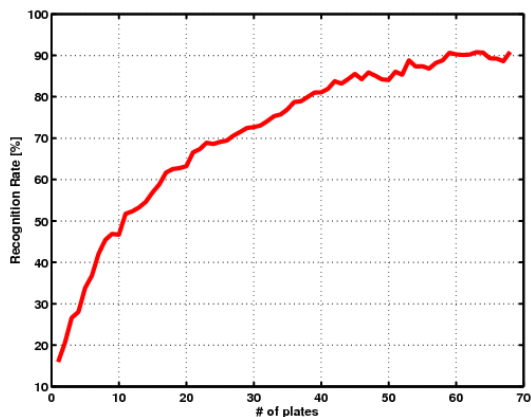
## Character Image Database

Support vector machines are trained on approximately 2700 manually labeled images of characters which were automatically extracted from high resolution images of parked cars using the license plate detection algorithm. According to the resolution of the test video sequence we resized all character images to 28x28 pixels.

## Recognition Results

To evaluate the quality of the proposed framework we used it for recognizing license plates of 109 cars passing the video sequence area. Due to the low resolution and changing lighting conditions the average recognition rate for independent classification of every character in every detected license plate is only 23.23%. As a consequence, in a single image based license plate recognition approach only 23.23% of the cars are totally correct classified. But this is significantly improved by analyzing additional plate representations provided by the tracking scheme and combining the corresponding recognition results by the presented majority voting scheme. Figure 6 analyzes the increase in recognition rate by using more representations. As the number of tracked representations gets close to 70, the percentage of totally correct classifications reaches more than 90%.

By using all available representations for recognizing the plate of every car in the test sequence (70 representations) our framework classifies 94.65% of all cars totally correct which is a





Recognition rates of totally correct classified plates (plate level) and correctly classified characters (character level) for a single image based approach in comparison to our tracking based classification

	Single image approach	Tracking approach
Plate level	80.74%	<b>97.16%</b>
Character level	23.23%	<b>94.65%</b>

Our result for such a challenging data set. Please note, that no postprocess-checking the validity of license plates according to syntax restrictions, Table 2 analyzes the recognition rate on plate level, i. e. the number of correctly classified plates, and character level, i. e. the number of correctly classified characters, for the single image based approach in comparison to our tracking based approach. As can be seen analyzing several representations instead of a single representation significantly improves the recognition rate.

Conclusion

We have introduced a novel framework which allows detection, tracking and recognition of license plates. Detection is handled by analysis of Maximally Stable Region (MSER) detection results and does not require any learning. We introduced a robust tracking scheme, which provides accurate license plate localizations and segmented characters simultaneously. The experimental results showed that promising results are achieved on a challenging data set. The robust tracking approach significantly improves the recognition rate. Furthermore, due to the high efficiency of the individual components, the framework can be used for real-time traffic video sequence analysis. To make the framework applicable in industrial scenarios, we also ported it to an embedded platform. Although the experiments were all performed on a desktop computer, the results also hold for a fully embedded implementation.

Acknowledgements

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I. Donoser, C. Arth, and H. Bischof

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