# Text based maximally stable extremal regions to detect vehicle plate location 

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#### Abstract

The license plate recognition strongly support intelligent infrastructure systems, such as toll and parking payment application, toll monitoring application, traffic monitoring application, and so forth. Although it has shown promising performance, but some method may fail in a more complex situation, because of the complexity of such variation of the position and orientation of the plate, different illumination, different backgrounds, and objects of non-plate. For efficiency higher visual matching, some fast keypoint detectors and corresponding descriptions have been carried out in several research, such as FAST, SURF, BRISK, Harris Corner feature. In general, plate detection systems have two problems, namely where the plate is and how big is its size. In this paper, we present the number plate localization method based on text segmentation of unstructured standard plates. The algorithm is capable of detecting large number of candidate text regions and progressively removing those that tend not to contain text. The experimental results show that from 16 images with size $4208 \times 3120$ pixels with a complex background is $87.5 \%$ accuracy, and the average detection time is approximately 33.25 seconds. Based on the results, the MSER feature detector can find the text area well. It holds consistent color and high text contrast.


Keywords: license plate recognition, plate location detection, text regions, feature detector

## 1. INTRODUCTION

The intelligent transportation system is now beginning to grow. Some applications supporting intelligent infrastructure systems include electronic payment applications (such as tolls and parking), toll road monitoring applications, traffic monitoring applications, and others. One aspect of the intelligent infrastructure support system is how to recognize a vehicle.

Vehicle license plate recognition is an important function of this system, and is an important part of our everyday lives. Based on observations, the vehicle plate has enough edges and angles of information, using edge detection, projection and morphological filters [1]. Although many of the Platform Introduction methods have shown promising performance in constrained environments, the same technique may fail in more complex situations due to complexity such as position variation and plate orientation, uneven lighting, multiple backgrounds and non-plate objects [2].

Several studies to improve plate recognition performance are focused on finding strong visual feature descriptions for changes in the environment and the plate itself. Over the last decade, a keypoint-based approach has been widely applied to visual matching [3]. One of the most successful examples is the Scale Invariant Feature Transform (SIFT) feature [3]. In this case invariant for scale and rotational changes are able to get promising results in many cases [4]. According to the results reported in reference [1][5], the SIFT-based method has been shown to detect the plate in various situations. However, for applications that require fast processing, such as mobile phones, SIFT does not meet the efficiency requirements due to comparatively slow computing speed.

For higher visual matching efficiency, several rapid keypoint detectors and appropriate descriptions have been proposed, such as the Robust Features-Robust Features feature (SURF) [6], Binary Robust Invariant Scalable Keypoints (BRISK) [7], Harris Corner [8] and so forth, which theoretically can increase computing efficiency when applied to a vehicle number plate recognition.

In general, plate detection systems have two problems, namely where the plate is and how big its size. Typically, the position of the candidate characters in the plate is first identified, and the box area of the plate is determined later. Based on observations [9] that certain characters on different number plates can be considered as duplicates of each other, the arc model based on local features for the proposed plate detection. Because the visual words generated from the unsupervised grouping are sensitive to the noise feature of the background image.

In this paper, we focus on step detection plate location. We present the number plate localization method based on text segmentation of unstructured standard plates. In the Maximally Stable Extremal Regions (MSER) method, this character recognition algorithm detects a large number of candidate text regions and progressively removes those that are less likely to contain text. The performance of the proposed system is tested on our own set of image data.

## 2. MAXIMALLY STABLE EXTREMAL REGIONS

Maximally Stable Extremal Regions (MSER) algorithm is basically region detector. The MSER calculation basis begins by selecting or sorting the order of pixels from low intensity to high intensity or vice versa (eg in grayscale images having intensity ( $0, \ldots$... 255) ). MSER is widely used in text localization and recognition applications. In MSER, the process of selecting pixels becomes a set of regions based on the threshold of binary intensity. Areas with the same pixel value at the threshold value in the connected component pattern are the values that are considered to be most stable (maximally stable).

The MSER feature detector works well to find the text area [10]. This works well for text because consistent color and high text contrast leads to a stable intensity profile. In Figure 1 is presented the MSER workflow.


Fig. 1 MSER Workflow

The Maximally Stable Extremal Regions (MSER) algorithm consists of several major stages:

1. Sorting all pixels by intensity.
2. Placing the pixels one by one (in the order of intensity) in the image, and renewing the component link structure, coming from extremal areas
3. Calculates the area variation of any extremal areas. Using the formula:
var $_{i} \frac{\text { Area }_{1+\Delta}-\text { Area }_{i}}{\text { Area }_{i}} / *$
4. Where i represents extremal areas with the highest intensity values and $i+\Delta$ refers to the extension of the i -area, with the maximum intensity of $i+\Delta, \llbracket v a r \rrbracket ~ i$ is the relative difference of the area where there is the highest intensity from $i$ to $i+\Delta$.
5. Through the order / extent of extremal areas. Look for one maximally stable extremal that has the smallest "var" of the main level.

## 3. DETECTION PLATE LOCATION

Steps for location plate detection are presented in Figure 2. The input image is made into grayscale, then imclose and imopen morphology is performed. After that detection of text area using MSER [10], because the consistent color and high contrast of text leads to stable intensity profiles. Then carried out the process of non-text area removal based on basic geometric properties.


Fig. 2 Flowchart System
Although the MSER algorithm selects most of the text, it also detects many other stable areas in images that are not text. A simple rule-based approach is used to filter non-text regions based on geometric properties. There are several geometric properties to distinguish between text and non-text [2,3], namely: Aspect Ratio, Eccentricity, Euler Number, Extent, Solidity. In MSER regionprops is used to measure some of these properties and then remove the region based on its property values. After that merge the text area to detect the location of the plate. One approach to combining individual text areas is to first find the neighbors text area and then form a bounding box around this region. To find neighbors areas, expand the delimiters calculated previously with the region.

Once the text regions are identified, a suitable geometric context is used to locate the plate. A bounding box will be estimated to cover the plate by defining the top, bottom, left, and right borders in sequence. After that, we get a rough estimate of the left and right boundary lines. On the plate, the ratio of plate width to height is constant. When the height of plate $h$ is predicted, $w$ wide plate can
also be obtained.

(a)

(c)

(b)

(d)

(e)

(a)

(b)

(c)

(d)

(e)

(f)

Fig. 2 Input Image (a), Grayscale (b), Morphology (c), Candidate Text Regions (d), Plate Location (e), Cropping Result (f).

## 4. EXPERIMENTAL EVALUATION

To perform testing in this study the authors use the application Matlab R2015a and notebook with the specification of Intel Core i3-3217U @ $1.60 \mathrm{GHz} 1.60 \mathrm{GHz}, 3 \mathrm{~Gb}$ RAM.

Table 1 Testing Result Sample

| Image <br> Number | Result <br> (s) |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Time Image <br> Number  | Time <br> (s) |  |  |  |  |
| 1 | 1 | 34.07 | 9 | 1 | 32.53 |
| 2 | 1 | 33.59 | 10 | 1 | 33.30 |
| 3 | 1 | 31.87 | 11 | 1 | 32.84 |
| 4 | 1 | 32.12 | 12 | 0 | 34.13 |
| 5 | 1 | 33.54 | 13 | 1 | 33.61 |
| 6 | 1 | 34.03 | 14 | 1 | 32.84 |
| 7 | 0 | 33.95 | 15 | 1 | 33.28 |
| 8 | 1 | 32.50 | 16 | 1 | 33.80 |

In Table 1, it can be seen that from 16 images sample data there are 14 images that can be detected plate location. Thus the value of the success accuracy of $87.5 \%$ and with an average computation time of 33.25 seconds.

## 5. CONCLUSION

Based on the testing results, the MSER feature detector can find the text area well. It holds consistent color and high text contrast. Therefore high-resolution number plates and various backgrounds can be done effectively. The experimental results show that from 16 images with size $4208 \times 3120$ pixels with a complex background detection the accuracy is $87.5 \%$, and the average detection time is approximately 33.25 seconds.

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