Locate My Plate
A License Plate Localisation System

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1 Introduction

This report describes the implementation of a robust, real-time License Plate Localisation system (LPL) [1, 2]. We analyze which characteristic features are important for license plate localisation. Using supervised learning, the system generates a cascading classifier which consists of layers that each hold one strong classifier. A strong classifier is a linear function of several weak classifiers obtained by boosting. Each weak classifier is a feature which describes characteristics of a license plate. Section 2 describes the data used for our experiments. Section 3 describes the features and how they are generated. Next the training and classification of weak-, strong- and cascading classifiers are both explained. Finally the results are shown and we come to the conclusions.

2 Dataset

The dataset used is obtained from [3]. It contains 246 car images with a resolution of approximately 640×480. The images are annotated on location and size of the license plate and were rescaled by 50%. The dataset is divided in a train-, test- and validation set with 159, 40 and 47 images respectively.

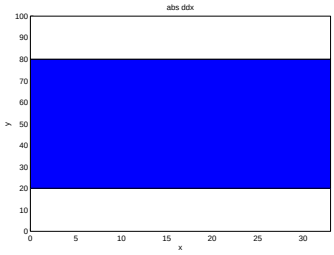
3 Features

The core of the LPL system consists of features as described by [1, 2, 4]. Features are image filters applied on a certain type of image (e.g. an x-derivative) see Figure 1. Formally a feature f is a tuple $\langle i, B, o \rangle$ defined as:

- i, an index corresponding to the image type.
- B, the set of blocks where each block $b \in B$ contains a sign $b_s \in \{-1, 1\}$ indicating subtraction or addition of that block and positions $b_{pa}, b_{pb} \in [0, 1]$, determine the relative block position within the feature.
- o, the orientation of the feature blocks: horizontal or vertical.

The feature value $f : x \mapsto \mathbb{R}$ of an image x is shown in Algorithm 1.

(a) The original image.



(b) The feature, internally represented as binary 01110.

(c) The feature applied.

Figure 1: A horizontal, second order x-derivative feature with binary code 01110, consisting of three blocks applied to an image.

Algorithm 1 featureValue(f, x, w, h): Returns the image $V = f(x)$

Require: The feature $f = \langle i, B, o \rangle$, the image x, the width w and height h of the feature.

Initialize V as an image with dimensions $D(x) - [w, h]$ consisting of zeros.
Let I be the i^{th} image type of x.
if o is horizontal **then**
    $I \leftarrow I^\top$
    Swap w and h
end if
Let B' be the set of blocks with rescaled coordinates using w, h.
for all $b \in B'$ **do**
    Let X be the result of applying b to I while respecting b_{pa}, b_{pb} alignment.
    $V \leftarrow V + b_s \cdot X$
end for
return V

3.1 Image Types

For this report, the following image types were used.

- 1st order derivative in both x and y directions.
- 2nd order derivative in both x and y directions.

Before applying the feature, the above image types are passed through an absolute filter. By calculating an integral image [5] per image type, the featureblocks can be calculated very efficiently as each block calculation requires only four array access instructions.

3.2 Generation

By representing a feature as a binary string, the set S of possible features can be easily calculated:

$$S = \{b(x, n) | \forall x \in \{1, \ldots, (2^n - 2)/2\}\},$$

where $b(x, n)$ represents x as a binary string of length n as the number of segments. Note that binary strings $0_1, \ldots, 0_n$, $1_1, \ldots, 1_n$ and the inverse binary strings are ignored. Each element in the binary string $s \in S$ represents the position and the sign of a feature segment. Adjacent segments that share the same sign are merged together and are called a feature block.

The horizontal features are generated using the transpose of the vertical features and by swapping the dimensions. The width and height of the feature are normalised, i.e. set to 1 so they can be generaly rescaled to different license plate dimensions.

4 Training

The overall cascading classifier consists of three types of training. The first type is the training of the weak classifiers using features. The second type is a linear combination of one or more weak classifiers into a strong classifier using a boosting algorithm. The third type is a cascading classifier with a strong classifier on each layer.

4.1 Weak Classifier

A weak classifier consists of a feature f, a threshold $t \in \mathbb{R}$ and an operator $\circ \in \{<, >\}$ which separates positive and negative samples according to the trainings set. After training, the weak classifier C constructs a binary image $B = t \circ f(x)$, where x is the image and f the function that returns the value of the feature as described in Section 3. The locations of the ones in B correspond to the location of possible license plates.

4.2 Strong Classifier

By combining weak classifiers, a strong classifier can be formed. This is the principle of boosting. A strong classifier is constructed according to the boosting algorithm adaboost, described by [5]. Adaboost is adaptive (hence the name) with respect to the weak classifiers it selects. By updating two sets of weights, those on the weak classifiers (α) and those on the training samples. Classification is performed as follows:

$$C(x) = \begin{cases} 1 & \sum_{i=1}^{N} \alpha_i \big(t_i \circ_i f_i(x)\big) \geq \tau \sum_{i=1}^{N} \alpha_i \\ 0 & \text{otherwise} \end{cases}$$

where N is the number of weak classifiers as selected by the boosting algorithm and $\tau \in [0, 1]$ a threshold which allows for changing the false positive- and detection rate.

4.3 Cascading Classifier

The cascading classifier is the final classifier. This classifier is trained as described in [5]. By specifying a false positive rate per layer, a detection rate per layer and a false positive rate goal, the algorithm constructs a cascade of strong classifiers using the training- and validation set. Algorithm 2 shows the classification of an image using a trained cascading classifier. The strong classifier $c_s \in C$ classifies according to Section 4.2, while respecting the previous false positives and true positives only. This results in a binary image B' which is logically 'anded' with the previous binary image B resulting in less false positives after each iteration.

5 Results

For our experiments we trained the cascading classifier using $fp = 0.99, d = 0.999, fp_{min} = 0.001$ for the false positive rate, detection rate and minimal false positive rate respectively. Furthermore we generated features consisting of 5 segments. The total number of features generated was $\frac{(2^5-2)}{2} \cdot 2 \cdot 4 = 120$. The final cascading classifier contains five layers with $1, 4, 14, 7, 10$ features respectively. An example of the cascading classifier is displayed in Figure 3. To illustrate how a layer is constructed, the strong classifier of layer 2 is shown in Figure 2. The confusion matrix on the test set can be found in Table 1.

Algorithm 2 cascadingClassify(C, x, w, h): Returns the binary image B of x

Require: C the cascading classifier, x the image, w, h the dimensions of the features

1: Initialize B as an image with dimensions $D(x) - [w, h]$ consisting of ones.
2: **for all** $c_s \in C$ **do**
3: $B' \leftarrow c_s(x|B)$
4: $B \leftarrow B \wedge B'$
5: **end for**
6: **return** B

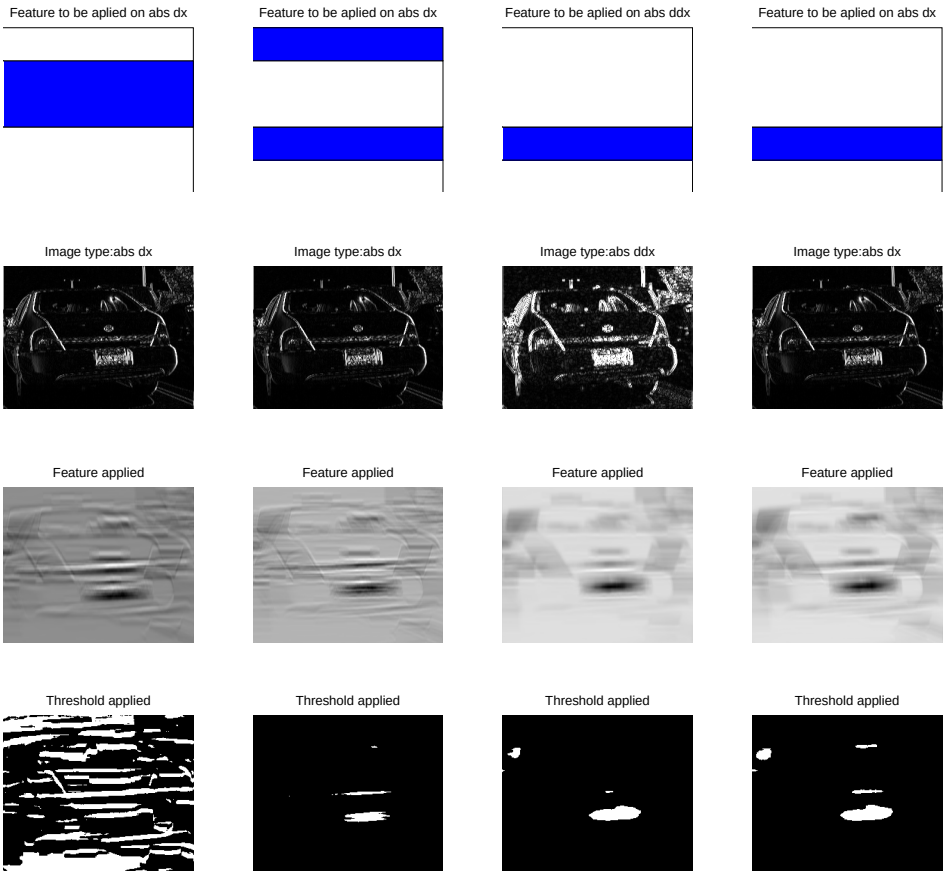


Figure 2: Example of the strongclassifier in layer 2 with 4 features. The first row shows the features, the second the image types, the third shows the features applied to the image types and finally the bottom row shows the thresholds.

An overall detection rate of 0.925 and false positive rate of 0.0648 was achieved. Figure 4 shows the averaged false positive rate per layer in the cascading classifier. Note that we experimented with just four image types as described in Section 3.1, using more advanced image types as described by [4] would decrease the false positive rate even further. A final result of the applied cascader can

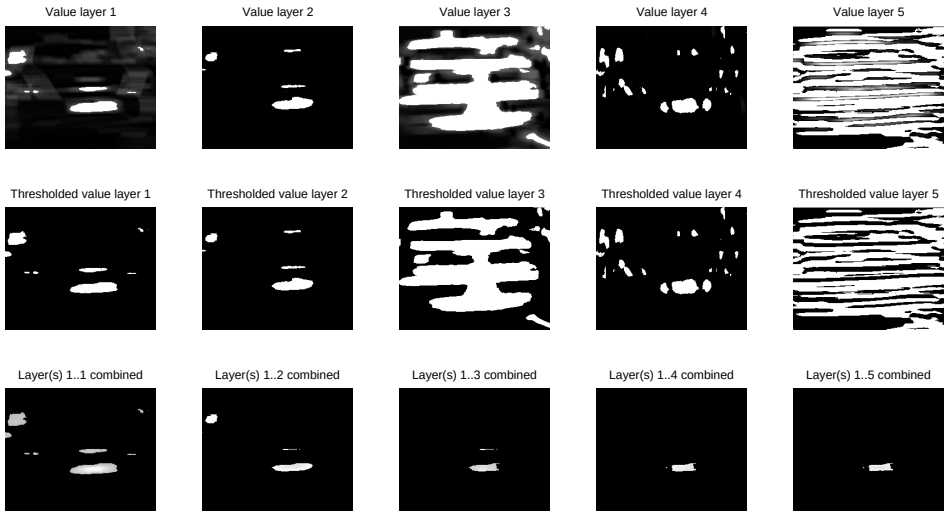


Figure 3: Example of the resulting cascading classifier with 5 layers. The first row shows the values of the strong classifiers, the second row shows the thresholds of the strong classifiers. The bottom row shows the actual cascading result, where each increasing layer more false positives are removed.

37	166186
3	2399245

Table 1: The confusion matrix of the test set.

be found in Figure 3.

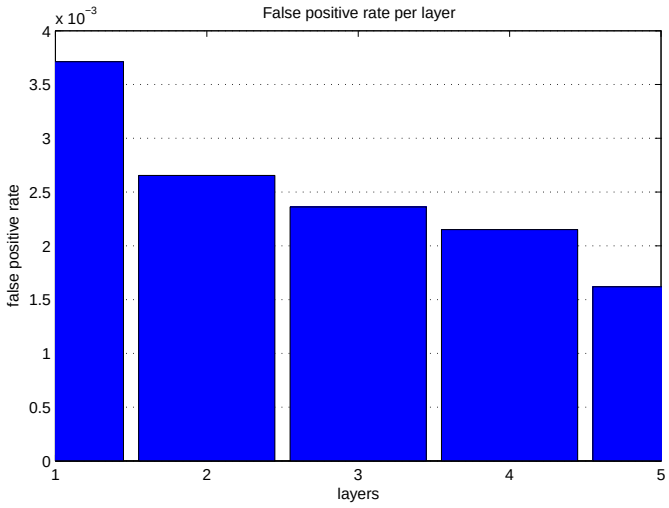


Figure 4: The false positive rate per layer, averaged over the test set.

(a) The original image

(b) The cascader applied, every white pixel is the upper left prediction of a license plate

Figure 5: An original image of a car and the resulting binary image after cascading.

6 Conclusions

Given just four types of images, the cascading classifier performs very well. With a detection rate of 0.925 and false positive rate of 0.0625 we can conclude that License Plate Localisation can be effectively achieved using this method. Even when no more sophisticated image types are used, the cascader could be used by a License Plate Recognition system as the remaining false positives can be filtered out by optical character recognition and the characteristics of a license plate.

7 Future work

On our experiments only four image types were used. Better results could be achieved when applying the features on more image types (e.g. variance, gaussian, colorchannels). Some of these new image types may be more expensive to compute and should therefore be used in the layers near the end.

The dataset provided contains tagged images, thus the license plate dimensions are known. In a real world system these dimensions could be anything. A solution for this would be the multi-scale approach. Apply different scales to the cascading classifier, starting with the biggest.

References

[1] L. Dlagnekov, "Video-based car surveillance: License plate, make, and model recognition," Master's thesis, University of California, San Diego, 2005.

[2] H. Zhang, W. Jia, X. He, and Q. Wu, "2006, learning-based license plate detection using global and local features," *Proceedings International Conference on Pattern Recognition, page to appear*, 2006.

[3] L. Dlagnekov and S. Belongie, "Ucsd/calit2 car license plate, make and model database," Tech. Rep., 2005.

[4] X. Chen and A. L. Yuille, "Detecting and reading text in natural scenes," in *Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on*, vol. 2, 2004, pp. II–366–II–373 Vol.2. [Online]. Available: http://dx.doi.org/10.1109/CVPR.2004.1315187

[5] P. Viola and M. J. Jones, "Robust real-time face detection," *International Journal of Computer Vision*, vol. 57, no. 2, pp. 137–154, May 2004. [Online]. Available: http://dx.doi.org/10.1023/B:VISI.0000013087.49260.fb