# 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

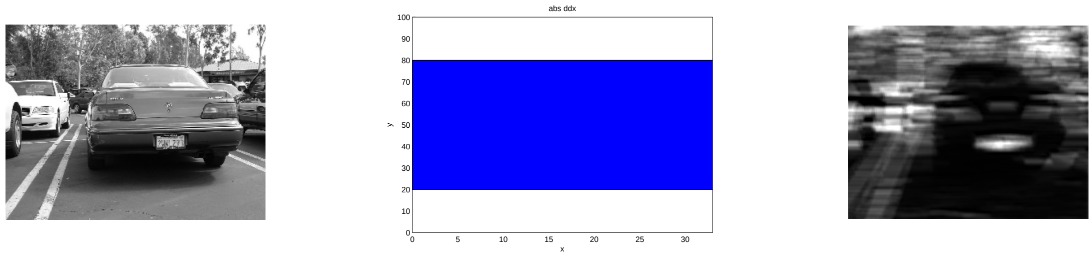
The dataset used is obtained from [3]. It contains 246 car images with a resolution of approximately $640 \times 480$. The images are annotated on location and size of the license plate and were rescaled by 50%. The dataset is divided in a train-, test- and validation set with 159, 40 and 47 images respectively.

## 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. (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.

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

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**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** $V$

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### 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 per image type, the featureblocks can be calculated very efficiently as each block calculation requires four array access instructions [5].

### 3.2 Generation

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

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

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. This set of features is duplicated for each image type.

# 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, 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

A strong classifier is constructed according to the boosting algorithm described by [5]. By re-weighting the positive and negative samples after greedy selection of a weak classifier, the algorithm selects the next 'best' features with their respective weight, $\alpha$. 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. 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.

**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: $B' \leftarrow c_s(x)$
4: $B \leftarrow B \wedge B'$
5: **end for**
6: **return** $B$

# 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. 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 5. To illustrate how a layer is constructed, the strong

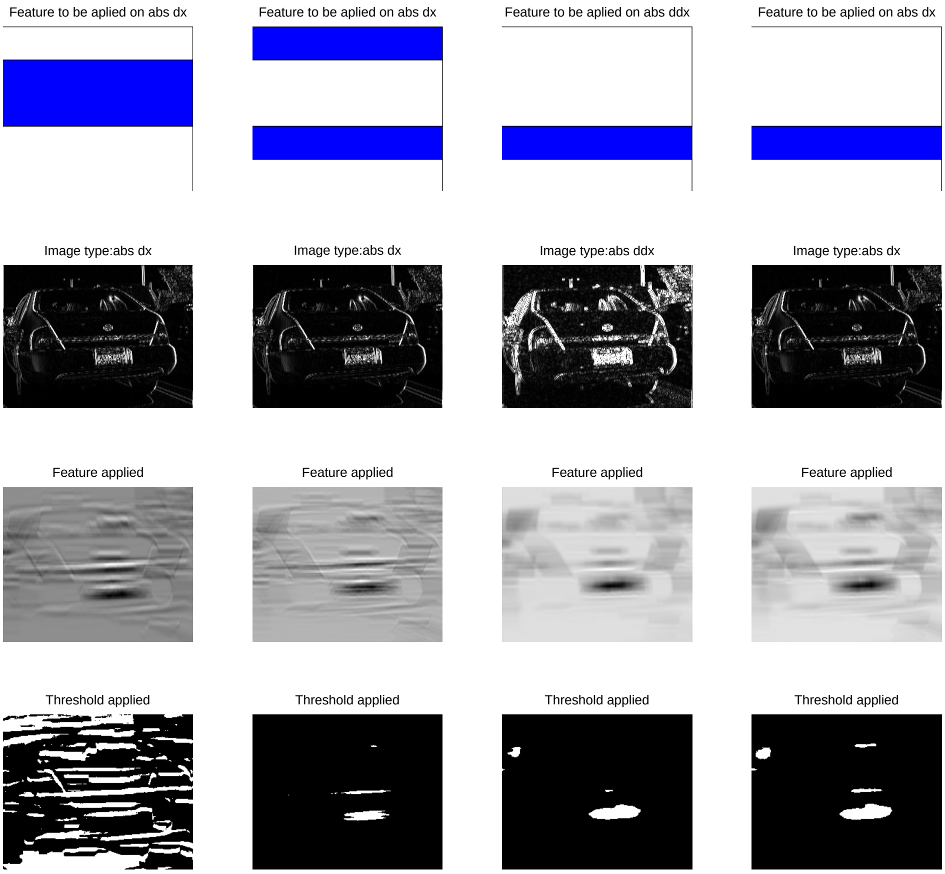


Figure 2: Example of the strongclassifier in layer 2 with 4 features.

| | |
|---|---|
| 37 | 166186 |
| 3 | 2399245 |

Table 1: The confusion matrix of the test set.

classifier of layer 2 is explained in Figure 2
The confusion matrix on the test set can be found in Table 1.

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 be found in Figure 5.

## 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

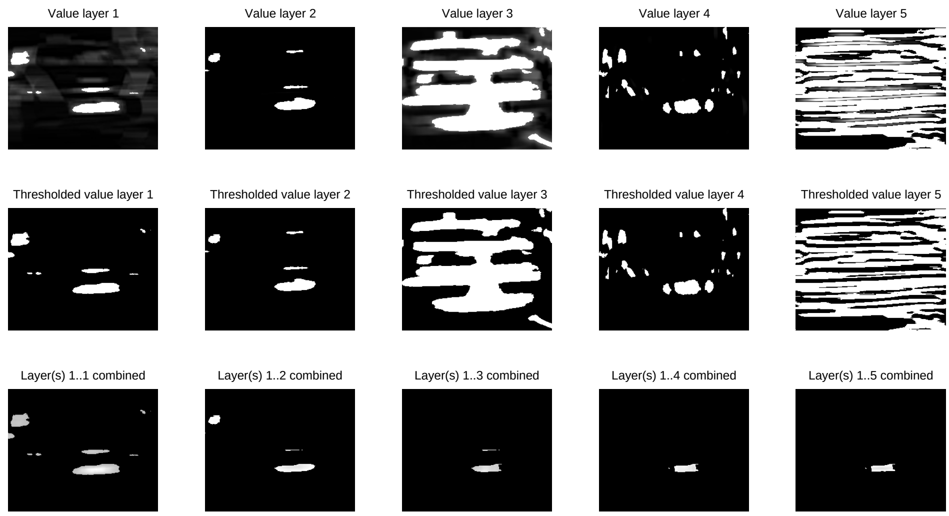


Figure 3: Example of the resulting cascading classifier with 5 layers.

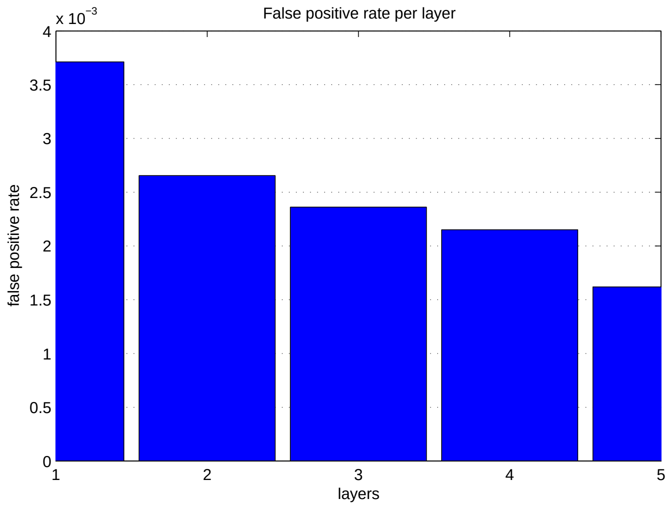


Figure 4: The false positive rate per layer, averaged over the test set.

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.


(a) The original image (b) The cascader applied

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

## References

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