# Color Mixture Based Segmentation for Vehicle License Plate Recognition

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## Abstract

We describe the current state of research and development of a system for the automatic segmentation of number plates of vehicles. The main source of information that is used to find the candidate areas is a mixture model of chromaticity values present in the bi-color plates.

## 1. Introduction

The automatic recognition of number plates of vehicles is a practical problem with many interesting applications. [1] reports a 91% recognition rate of a vehicle identification system placed on Italian highway tollgates. [2] is divided into the modules of Car Detection, Segmentation and Recognition. A similar divide-and-conquer organization be be observed in most systems, for instance [3].

Monochromatic pixel intensity gradients is a main feature for license plate segmentation. [1] exclusively uses the maximum local gray scale gradient. [4] uses gray scale morphological operators to isolate the plate region, see also [5]. [6] explores the Generalized Symmetry Transform in gray scale, [7] uses simple monochrome histogram based segmentation to find the plate. The use of chromaticity based information can be observed in a relatively limited number of publications, e.g. [8] which explores the fact that Korean plates have white symbols on green background. The consideration of bimodal color occurrences in the plate is the main approach for segmentation presented here.

## 2. Plate Segmentation System

We concentrate our research on the plate segmentation which we judge as the most critical module in a complete vehicle recognition system. Our system looks for areas of transition from plate background to plate symbols. Therefor the first step is a color gradient analysis of the original image. Then the edge pixels are classified if they belong to one of the two colors present in the plate. This is essentially the approach of [8] which use a Perceptron with one hidden layer to classify individual pixels of Korean plates in HLS color space, for instance white symbols on green background. Now these candidate pixels are analyzed if in their neighborhood does occur a mixture of the two plate colors by scanning small masks around the candidates. If a bimodal mask has been found we suppose to have found a pixel in a transition are within the plate. The standard geometric features (for instance aspect ratio) are used to further limit the plausible plate region.

## 3. Color Model for Plate Segmentation

The values of the pixel at position $(i, j)$ are considered a vector of RGB values $\mathbf{f}(i,j) = \left[\begin{array}{ccc} r(i,j) & g(i,j) & b(i,j) \end{array}\right]^{\mathrm{T}}$. Chromaticity analysis of $T^2$ pixels of an odd sized $T \times T$ neighborhood (mask) is performed with position $(i, j)$ as the center. Let us assume that $(i, j)$ lies in a transition area inside a plate between background and symbol colors with a sufficient large number of pixels from both groups. Then there is reasonable believe that the pixels $\{\mathbf{f}_k\}_{t=1}^{T^2}$ of the mask obey a 3-variate bimodal probability density distribution. One mode $\boldsymbol{\mu}_b$ is defined by the expected value of the background color, the other $\boldsymbol{\mu}_s$ by the symbol color.

### 3.1. Chromaticity Feature Model

The final feature vector $\mathbf{x}$ of the $T \times T$ local region is the concatenation of the individual color components $R$, $G$, $B$ of the two RGB modes $\boldsymbol{\mu}_b$ and $\boldsymbol{\mu}_s$ as

$$\mathbf{x} = \left[\begin{array}{cccccc} \mu_b^{(r)} & \mu_b^{(g)} & \mu_b^{(b)} & \mu_s^{(r)} & \mu_s^{(g)} & \mu_s^{(b)} \end{array}\right]^{\mathrm{T}}. \quad (1)$$

One crucial problem is how to determine the two modes $\boldsymbol{\mu}_b$ and $\boldsymbol{\mu}_s$. We use $K$-means clustering [9] with very few iterations to calculate the modes, with two initial cluster centers set to the previously defined mean values of the symbol and background colors.

### 3.2. Classifier Model for Chromaticity Features

We use manually segmented masks from the plate to calculate the patterns of the *plate* class. The regions outside the plate are considered the *not–plate*. In order to compensate for the small number of *plate* class feature vectors we use a Bayesian maximum likelihood classifier [9] with decision functions

$$d_i(\mathbf{x}) = p(\mathbf{x}|C_i) \tag{2}$$

where $p(\mathbf{x}|C_i)$ is the class conditional probability density of feature value $\mathbf{x}$ given class $C_i$. Continuing the assumption of Normal distributions of the feature values we model the class conditional densities as

$$p(\mathbf{x}|C_i) = -\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^{\mathrm{T}}\boldsymbol{\Sigma}_i^{-1}(\mathbf{x}-\boldsymbol{\mu}_i) - \frac{1}{2}\ln|\boldsymbol{\Sigma}_i| \tag{3}$$

where $\boldsymbol{\mu}_i$ and $\boldsymbol{\Sigma}_i$ are the class specific mean vectors and covariance matrices.

## 4. Plate Segmentation System

A more detailed description of the processing sequence is presented. In the gradient analysis of the original image the gradient $\nabla \mathbf{f}(i,j)$ vector composed of the magnitude of the gradients of the individual RGB bands is calculated by a modified form of the Prewitt operator masks [10]

$$\nabla_x f \equiv \begin{vmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{vmatrix} \quad \nabla_y f \equiv \begin{vmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & -1 & 0 \end{vmatrix}.$$

which diminishes the influence of the vertical gradient and empirically seems to improve the segmentation. The magnitude of the gradient of each RGB component is usually [10] approximated as $||\nabla f(i,j)|| \approx |\nabla_x f(i,j)| + |\nabla_y f(i,j)|$. Candidates pixels at $(i,j)$ for the following color classification and region expansion are only considered if the length of the vector of the magnitudes of the gradients of the three bands is larger than a predefined threshold $T$ as

$$|| \begin{pmatrix} ||\nabla r(i,j)|| \\ ||\nabla g(i,j)|| \\ ||\nabla b(i,j)|| \end{pmatrix} || > T. \tag{4}$$

After the pixels with a high gradient have been determined they are submitted to a classifier which decides among *three* classes: *background*, *symbol* and *neither–background–nor–symbol*. For instance in Brazilian plates the symbol color would be black, the background color of the plate would be gray and any other color belongs to the third class. In order to obtain the training samples for these classes we use the same plate regions that were used for the calculus of the two RGB modes $\boldsymbol{\mu}_b$ and $\boldsymbol{\mu}_s$ in (1). We measure the Euclidean distance of the RGB value of the individual pixel to the modes, decide to which of the two it belongs and generate a training sample. All other pixels outside the plate deliver samples for the third class which is neither background nor symbol.

Candidates at $(i,j)$ that are filtered by the gradient criterion (4) and the individual pixel classifier are then used as the centers of the $T \times T$ masks which extract the feature vector $\mathbf{x}$ defined in (1). If the classifier (2) decides that the pixel at $(i,j)$ is a plate seed, a region expansion takes place. Recursively all the 4-neighbors of a recognized plate seed are classified by (2) until no more plate seeds can be traced. This process delivers 4-connected contiguous plate candidate regions.

Finally a geometric feature plausibility analysis is performed. For instance the aspect ratio of the contiguous region must be similar to the one of a plate or the segmented region can be expected in a central region of the image.

## 5. Experimental Results

A randomly selected subset of $140$ images of the license plate database described in [5] was split into $50\%$ training data and $50\%$ test data. We strictly separated the test data from the training set, i.e. no system parameter was ever influenced by any of the test images. An illustrative example of the individual processing steps is pointed out in figure 1. The threshold for the gradient segmentation (4) was set to 300.

From the total of $70$ training images the area of the central license plate was segmented giving a $N \times M$ subimage with values $M$ and $N$ eventually different for each image. The size of the neighborhood mask that was used to to obtain the color mixture of the pixels was fixed to $T = 11$ delivering $121$ RGB values of the pixels within the mask. In figure 1 a.) three of such masks are drawn within the original image, being one a true transition area within a plate and the other two outside. The result of the clustering algorithm to obtain the two modes to form the feature vector $\mathbf{x}$ of (1) is presented in figure 2. For illustrative reasons the pixel of all three masks were merged into the same graph in order to show the difference of the RGB values. The figure shows the $121$ pixels of the three regions highlighted in figure 1 a.) in RGB space: The first mask is within the red car, the second picks a part of the yellow stripe and the gray concrete and the third mask is within the plate of the main car. For illustrative reasons the masks are shown within the same graph. Together with the $121$ pixels the two cluster centers are shown with are determined by the clustering algorithm.

The manually segmented plate areas of the training images are used to acquire the masks which deliver the two modes in transition areas. The mode values are then concatenated to form the feature vector. Each plate region of dimension $N \times M$ is scanned by column and row, pixel by pixel, giving $(N-T+1)(M-T+1)$ masks of size $T \times T$, giving a statistically quite significant size of 36382 sample vectors $\mathbf{x}$. Outside the plate the scanning is done by skipping $T$ pixels (taking the masks side by side from the regions outside the plate) totaling 207340 samples. The $K$-means clustering is applied to each of the masks to calculate the two modes. Usually the clustering takes only three iterations because of the existence of only two centers which define the modes. With the 6-D feature vectors the maximum likelihood classifier (2) is trained. In parallel the masks were used to extract the samples for the individual pixel classifier. Each pixel is attributed to one of the two clusters (symbol and background in the case of the plate mask and neither background nor symbol clusters for masks outside the plate) and attributed the respective class (*background* (45911 samples), *symbol* (52821 samples) and *neither–background–nor–symbol* (215110 samples)).

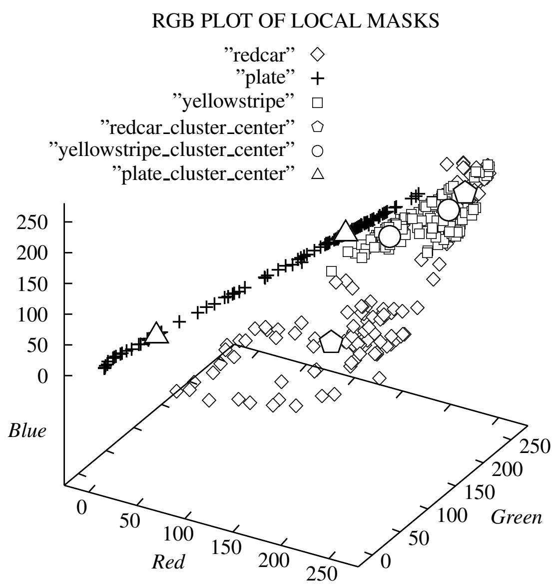


Figure 2: Pixels of the three masks highlighted in figure 1 a.) together with the two cluster centers of each mask.

For the plausibility analysis we defined the following rules: 1.) Only areas over 700 pixels were considered to be a plate candidate; 2.) Width more than 60 pixels; 3.) Height more than 12 pixels; 4.) Within a border that excludes 5% of the height on top and the bottom and 5% of the width on the right and left sides; 5.) Finally the aspect ratio must be between 2 and 8.

The results of the segmentation process are outlined in table 2. Since the correlation of successful segmentation and the size of the plate are notable we distinguished two groups of plates related to their size (Small and Large). The results are quite encouraging. We must emphasize that the image database is extremely heterogeneous with many different parameters, like illumination position, angle, state of the plate and size. We can expect that in a more restricted acquisition context the results will show much higher success rates.

| *Processing stage* | Time | |
|---|---|---|
| | abs. [sec.] | % |
| Gradient calc. and thresholding | 1.85 | 0.84 |
| Individual pixel classification | 0.31 | 0.15 |
| Mixture classification & Region expansion | 217.26 | 99.01 |
| TOTAL | 219.43 | 100.00 |

Table 1: Processing times for the image of figure 1 on a 466MHz Celeron processor and Linux OS.

The results of the segmentation experiments using the test set are described in the following. The state of the plates of the test set was categorized qualitatively into four groups, *Good,* Skewed, *Faded Symbols and* Dirty, with 62, 2, 3, and 3 plates respectively. Processing times can be seen in table 1.

## 6. Conclusions and Future Research

The main contribution of this license plate segmentation system is the feature model based on a color mixture model and the specific choice of a parametric classifier able to deal with erroneously labeled samples. More restricted image acquisition conditions and additional geometrical constraints will be investigated to raise the accuracy.

## 7. References

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a.) b.)

Figure 1: Example result. a.) Original image with three $11 \times 11$ masks used for the determination of the two color modes. First mask "redcar" from rear part of small red car (right car of the three car group). Second mask "yellowstripe" from area of parking lot on the right side of the central vehicle. Third mask "plate" from transition area of license plate of the same car; b.) bounding boxes of plate candidates.

| *Segmentation Experiments* | Small | | | Large (Width > 80 pixel) | | | All images | | |
|---|---|---|---|---|---|---|---|---|---|
| | abs. | % group | % tot. | abs. | % group | % tot. | abs. | % | accum. % |
| Number of images | 22 | 100.00 | 31.43 | 48 | 100.00 | 68.57 | 70 | 100.00 | – |
| Zero plate pixels detected | 1 | 4.55 | 1.43 | 1 | 2.08 | 1.43 | 2 | 2.86 | – |
| Few plate pixels detected | 1 | 4.55 | 1.43 | 3 | 6.25 | 4.29 | 4 | 5.71 | 97.14 |
| Many plate pixels detected | 5 | 22.73 | 7.14 | 4 | 8.33 | 5.71 | 9 | 12.86 | 91.43 |
| Whole plate detected | 9 | 40.91 | 12.86 | 1 | 2.08 | 1.43 | 10 | 14.29 | 78.57 |
| BB of plate partially detected | 0 | 0.00 | 0.00 | 5 | 10.42 | 7.14 | 5 | 7.14 | 64.29 |
| BB of plate totally detected | 1 | 4.55 | 1.43 | 2 | 4.17 | 2.86 | 3 | 4.29 | 57.14 |
| Only rue plate segmented | 5 | 22.73 | 7.14 | 32 | 66.67 | 45.71 | 37 | 52.86 | 52.86 |

Table 2: Result of plate segmentation test. Two groups of test images *Small* and *Large*. Absolute values, within-group and total percentages shown. In cases where at least a part of the plate was detected accumulative values are also shown. For instance in 78.57% of the images the whole plate was successfully segmented which also implies that "many" and "few" pixels were detected (BB=Bounding Box).


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