License Plate Location and Recognition Using Decision Regions of Color with Genetic Algorithms and Neural Networks

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(Paper received on August 17, 2006, accepted on September 27, 2006)

Abstract. Automatic license plate location and recognition is an important field of opportunity for law enforcing. Cars involved in crimes can be located a lot faster by a spread number of cameras looking for them automatically than by visual inspection by police officers. This paper proposes a method for license plate location and recognition of moving vehicles with complex background. The license plate is located using color decision regions, with a two stage process using genetic algorithms and a multilayer perceptron neural network; finally individual characters are segmented using color and then a neural network is used to classify them.

1. Introduction

License plate recognition is an important research topic in computer vision nowadays. The applications range from traffic control, authentication to enter private buildings; to toll systems in paying parking lots.

The license plate recognition problem is always divided in two steps: license plate location and character recognition. For the location process, techniques such as vertical edge detection [12], color classification using a neural network [9], vector quantization [15], fuzzy logic [13], as well as directly looking for sequences of characters in the source image are used.

The recognition problem is usually further divided into two stages [2]: character segmentation and character recognition. Techniques often used for character segmentation include discrete time cellular network (DTCNN) [1], horizontal and vertical histogram accumulation through the slopes of vertical dynamic range [10] and horizontal and vertical component connection count. For character identification Jaccard value based templates [9], skeletization, intersection location and line tracing [3] and neural networks [2], among others were used.

Different approaches in literature, especially for license plate location, are not directly comparable due to differences in license plates in various locations throughout the globe and the different environments in which license plates are acquired.

Pan et al [6] use black, wide license plates (aspect ratio of about 4:1) with a thin white frame and white letters. Lim et al [3] use the same kind of license plates: Black, wide with a white frame. Their paper also assumes the license plate has been presegmented, their sample image shows the license plate up close with only some of the back of the car side showing. Zheng [12] recognizes the same kind of license plates. This paper does cover location and environmental noise. Brugge [1] uses a wide license plate with yellow, reflective and black letters in pairs. The sample images contain background information, however they are taken from a fixed location and therefore the background is static. Chang [2] reads white license plates with black numbers that have an aspect ratio of about 2:1. Chang uses a variety of angles and complex, real life backgrounds. Nijhuis [5] reads license plates with reflective yellow backgrounds, black numbers, wide aspect and a black thin border; also uses images where the car fits entirely in the scene but almost fills it, not leaving much background in the scene. Park [7] uses black tall license plates with an aspect ratio of about 2:1, white letters and a white border. Images where the car almost completely fills the image as well are used. Ryung [9] works with the same type of license plates: black, white letters, white border and 2:1 aspect ratio. The test images have a static background. Sirithinaphong [11] uses 2:1 license plates with white background and black letters without much environmental noise.

This paper proposes different hybrid methods for license plate location, and recognition with complex background. First, a license plate location method using vertical edge detection and aspect ratio information was tested. A second one that uses two different neural networks, one to perform color segmentation and the other one to identify license plate candidates. Finally, the third one uses a genetic algorithm to find Decision Regions of Color (DRC) in the RGB color space to perform color segmentation and then a neural network to classify this DRC is used. Then the recognition stage is done using a neural network.

The results of this paper, and other papers in literature, can not be directly compared because of the differences in the license plates as well as the differences of the environments under which the images of the plates are captured. Furthermore, some papers consider location or recognition of the plate only, not both.

2. Methodology

The proposed methodology is divided in four stages: preprocessing, license plate detection, character segmentation and character recognition. In the first two stages, it can be considered that the image may contain zero, one or more license plates, with natural (complex) backgrounds.

Three license plate detectors were proposed. The first license plate detector looks for vertical lines in the preprocessed image and then uses the aspect ratio information of the lines found to figure out where the plate may be; the second detector uses a neural network to convert the colors in the original image into predefined color classes; separating what is a license plate from what is not. Finally, for the third detector, a genetic algorithm was used to find a Decision Region of Color (DRC) in the RGB space that define the colors contained in the plates and finally the image was then segmented using those colors with a multilayer neural network perceptron.

The character segmentation module takes a license plate image and separates the characters using color information from the original image, together with an heuristic function to construct the complete characters with the lowest amount of noise.

The character identification module extracts a set of features from the segmented characters and uses them as input for a multilayer perceptron neural network for classification.

Fig. 1. This figure illustrates vertical edge detection. **A)** Original image **B)** Sobel operator **C)** Modified Sobel operator

3. Preprocessing

The contrast in the license plates that were being located is very low, so the images were first equalized. Then the image is converted to gray-scale, and then the vertical edges needed for locating the plates were extracted using a custom convolution kernel based on the Sobel operator. The known Sobel operator's convolution kernel was modified so that it smooths the image, and (as a side effect) slightly thickens the borders.

Due to the normalization of the image, an iterative binarization method based on two thresholds and 3 regions is proposed; the algorithm is a modified version of the iterative threshold selection method.

First an initial threshold value is obtained by the gray level image average, this value is used to divide the image in two different regions, further two different thresholds for each region are obtained, and also 3 different regions. This procedure is repeated until the threshold values do not change.

Finally, a simple noise reduction algorithm is applied to the binarized image to remove small and irrelevant objects that are generated by complex environmental conditions, by sliding a window and deleting any object that completely fits in it.

4. Proposed methods for license plate location

Three different methods for license plate detection were used to compare their performance. The first one is based on vertical edges detection, and the other two are color-based methods.

4.1. Vertical edges based method

This method let us extract candidate license plates from the noise reduced image, it consists in finding matching pairs of vertical lines with approximately the same height, *y* coordinates and separated by an aspect ratio of approximately 2:1. A variety of factors, including vanity plate holders, crooked license plates and noise in the acquisition stage, force to have very loose parameters for each step in this process, resulting in a high number of false positives, so this method is not described in detail in this paper.

4.2. Color based methods

These methods are based on the color of the license plates, and the DRC defined by that color in the RBG model. The image is color segmented according to colors that are known to belong to license plates, and colors that are known not to. Each license plate colored region is analyzed in order to extract features that describe its DRC. These features are classified by a neural network in order to determine whether they describe a license plate or not.

Two approaches were tried in constructing the DRC in the RGB color space. The first one built by hand and classified by a neural network; and the second one built automatically using a genetic algorithm and classified using a neural network.

4.2.1. Neural network based color segmentation

For the neural network based color segmentation, a hand crafted set of license plate colors was used, then a set of no license plate colors was generated automatically and both were used to train a neural network to classify both. This method is intended to identify license plates under the broadest possible spectrum of light sources and conditions; therefore the images were taken under direct and indirect sunlight, incandescent and fluorescent lights sources. The color set was obtained using 63 different images containing the rear license plate. The distance of the cars from the camera ranged from 1 to 7 meters. The lens' zoom was set at its furthest position.

License plates were extracted by hand from these images and collected together in a single mosaic image. Special attention was taken so that the plates were cut containing no regions of the image that don't strictly belong to the license plates; which means screws, vanity license plate holders and other objects were removed from the image even if they overlapped with the plate.

The number of colors in the image was then reduced from 24-bit color to 8-bit (255) and from there, colors belonging to the foreground (letters) and the background of the license plate were selected manually from the image's palette.

To generate the non license plate colors, the previous set was converted into a DRC in the RGB color space. The region is described by its vertices which are defined by the colors in the license plate background color set.

To construct the DRC, each of the colors in the set was tested against the rest. Every one of them that was not entirely contained by any other 4 colors in the set became a vertex of the region.

A big sample of colors was generated, and each of those tested for inclusion in the DRC. Any sample that was not completely included in the DRC or touched its borders was added to the non license plate colors set; if the sample was contained in the DRC, it was added to the enhanced license plate background color set; if the sample touched the borders of the shape, it was discarded because it was left up to the neural network to finely define the borders of the shape, and such samples would have over-trained it.

The non license plate color, enhanced license plate background color as well as the license plate foreground color sets were used as input to train a back propagation neural network with one hidden layer, 3 input nodes, 3 output nodes and 128 nodes in the hidden layer. The number of nodes in the hidden layer was determined experimentally. It was believed to be too big, but that configuration provided best results.

The neural network is then used to classify colors in source images to create regions of similar colors. Any region that belongs to the license plate background color set is considered to be a license plate candidate.

Fig. 2. This figure shows the license plate located and highlighted in white. A) Original images. B) Segmented images.

4.2.2 Genetic algorithms and neural network color segmentation

For the geometry based color segmentation, four *(x,y,z)* coordinates, that define a Decision Region of Color (DRC), were used to define the license plate background color set. The set was later fine tuned by adding intersecting regions that subtracted colors from the license plate background color set, adding them to the non-license plate color set.

In order to generate the DRC, a training set of 100 pictures of cars was taken from behind, under similar lighting conditions, with a range of distances from 5 to 8 meters and with the cars being at angles between 30 and 60 degrees relative to the camera. The pictures were taken under direct sunlight, between 11:00 and 13:0 during the spring.

The license plates were manually extracted from the images. Special attention was paid to making the cut leaving a buffer zone around the plates that could include non license plate colors; therefore the license plates themselves must never touch the edges of the cut images.

A genetic algorithm was then used to generate the DRC that would be used to classify the colors in the test images. The goal of the genetic algorithm is to find a configuration of DRC that is capable of finding the license plate in the biggest number of images possible while, simultaneously, making sure the license plate regions do not extend beyond their borders, invading zones of the image surrounding the plate (typically the trunk of the car).

Fitness function. In order to achieve this configuration, a fitness function was developed so that the algorithm can find a configuration by performing the following optimizations:

1) Maximize the size of the biggest region in each image. The biggest object should always be the license plate background, including the "angel" image in it. It may or not include the letters, but that isn't as important as they are separated in another stage in the process; even though it is still better if it doesn't because it means the color set fits the background colors more tightly, and will generate less false positives.
2) Minimize the amount of pixels of the biggest region that touch the borders of the image. That means that the license plate should be completely contained within the image and not bleed out, or at least be contained as much as possible. It is important to remark that this step doesn't imply minimizing the number of pixels of the license plate background set that touch the borders of the image; that is still possible especially for golden cars; the goal of this step is that the one object that is assumed to be the license plate should be separated from other objects that touch the border; despite the color set to which those belong.
3) Generate a small number of regions. So that both halves of the plate, and the "angel" (that divides those two halves of the plate) are covered by the color set. A potential side effect of this restriction is that the letters of the plate may be included in the wrong set; but as mentioned before that is not a big problem.

Encoding. The red, green and blue components of each color that define the vertices of the DRC were stored as real (floating point) numbers to have more precision when the colors are separated; especially considering that each solid is only defined by 4 points, and that makes it hard to include colors in the DRC when they're away from its center of gravity because the angles become too acute.

By using floating point numbers, and ranges that extend the intensity ranges of the image ([0,255]) more colors are possible to be integrated inside the sets.

Range and precision: The range of intensity values of each channel of the image is [0,255]. The DRC vertices are allowed to exceed these borders because of the limitations of the representation. Therefore, the range of values per coordinate per pixel that the genetic algorithm seeks was extended to (-256,512).

In order not to waste most of the generated individuals, the range is expanded in a zigzagging fashion. That is, after the bounds are exceeded, the direction of the numbers changes until it meets the opposite bound again. For instance, the number 513 is converted into 512 and so on.

The resulting DRC are then used to classify the colors in the source images as license plate or non license plate colors. With those, the DRC are grouped and later classified by a neural network as license plates or not, as mentioned above.

In order to determine whether a color is contained by one of the DRC, a plane is formed with 3 colors of the solid, then it is determined whether the remaining color is bigger or smaller than the plane using the straight line general equation; finally, it is also determined whether the color that is being evaluated is bigger or smaller than the plane. If the remaining color was bigger and the color being evaluated is smaller, or vice versa; the color is considered to be outside of the DRC; otherwise, the color is potentially included. The previous steps are repeated for all 4 possible combinations of plane - stray point colors. If the color is considered potentially inside for all combinations, then the color is determined to be contained in the DRC; otherwise it is not.

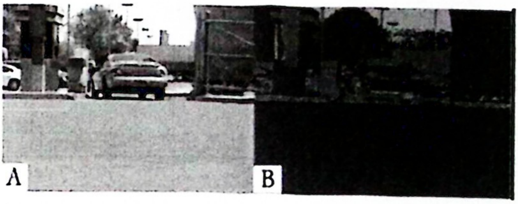

Fig. 3. This figure shows a failed color segmentation. **A)** Original image **B)** Color segmented image

Figure 2 shows an example of correct color segmentation of the license plate in three images under different lighting conditions and real life backgrounds. Figure 3 shows an example of an incorrect segmentation, where the color of the car is too similar to the color of the plate for it to be segmented.

5. Proposed method for license plate recognition

5.1. Character Segmentation

In this paper, a color-based image segmentation technique was used to separate the characters. Sixty sample hand-cut license plate images, taken in diverse lighting conditions were examined to generate a color table with the following categories: background colors, foreground colors, mostly background colors and mostly foreground colors.

The total length of the table became 156 colors; the table was further optimized by finding colors that are contained by sets of other colors in RGB space and eliminating them from the table.

In order to classify the pixels, the license plate images are analyzed pixel by pixel, finding the color in the table closest to the color in a pixel and then labeling it with the corresponding tag from the table. This generates an image with 4 different values, as shown in Figure 4.

In order to assign ambiguous regions to the foreground or the background, a number of combinations are tried and analyzed with a heuristic function; the regions are combined as follows, for every character found: (a) foreground is foreground and everything else is background, (b) foreground and "mostly foreground" are foreground and everything else is background, (c) background is background and everything else is foreground and (d) a number of randomly (probabilistically) generated combinations. The one with the best heuristic value is chosen as a character.

Fig. 4. This figure shows character segmentation. **A)** Original image **B)** Segmented image.

b) Feature extraction

Each character is first normalized to a fixed size and adjusted aspect ratio using continuous aspect ratio mapping [4], which was proved to be better than proportionally scaling the characters. The equation for continuous aspect ratio mapping can be seen in Equation 1, where r is the original image's aspect ratio and r' is the resulting image's aspect ratio.

$$r' = \sqrt{\sin\left(\frac{\pi}{2} r\right)} \tag{1}$$

A reduced Hough transform is used to identify horizontal, vertical, 45 degrees and 135 degrees lines. The three most populated lines are selected, and their origin, angle and number of votes are used as features, after sorting the lines to assure they are always used in the same order. The normalized distance of every white pixel from the center is calculated and used as another feature; and finally, the image is divided in 6 regions (in 2 horizontally by 3 vertically), and the distance from the points located at the center and edges of several of those regions to white pixels within those regions are calculated. The points are shown in Figure 5.

c) Character identification

For number identification a 2 layer, back propagation neural network was used with

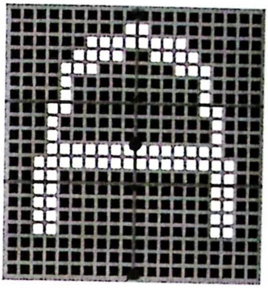

Fig. 5: Figure of feature points from which distance is measured

20 input nodes (corresponding to the 20 features extracted); 30 nodes in both hidden layers and 10 output layers.

6. Results

The vertical edges based method for license plate location had a success rate of 80% on the set of training images; however, the success dropped below 60% on test images due mostly to low contrast between the plates and the cars and it being overly sensitive to deformations on the edges of the license plate, often seen in Mexico city.

The color segmentation using a neural network had a success rate of 85% both on the training and test sets.

The performance of the neural network in the license plate recognition was improved when the genetic algorithm for DRC in the RGB color space was used, with success rate of 95% on the training images set, and 92% on the test set.

Both color-based methods are highly successful at finding plates when vanity license plate holders are installed, with success rates of over 99%.

Both methods have problems with certain kind of colors. The most problematic is golden, because it is similar to the color of the plate; under some lighting conditions it may appear identical to how the plate appears under other lighting conditions; thus, the plate is near impossible to extract from the car. Other problematic car colors are white and silver.

The recognition method had a success rate of 98% on numbers and 97% on letters. The character segmentation's performance can't be evaluated individually, because characters that may appear wrong visually were still recognized properly by the neural network.

Of the literature, the method presented by Zheng [12] can not be applied, and therefore fairly compared to the one presented in this paper because the complex backgrounds considered in this one would yield a high number of false positives with Zheng's edge counting method; Zunino [15] assumes the distance and position of the plate to be known, conditions that are not met in this paper. Ryung [9] utilizes a neural network to perform color segmentation of the source images, similar to the article, together with horizontal and vertical histogram count, the method isn't comparable to the presented one in this paper because it uses a pixel's neighbors' to perform the color segmentation, but because the size of the plate may be very big in this paper, if the plate is located near the camera, the pixel's neighbors may all be of one color, whereas Ryung's method depends on the neighbors having both background and foreground license late colors; finally, Lim's method looks for contiguous regions to look for characters directly on the image, which would be impossible to do under the environment of this paper because the contrast of the colors of the plate isn't enough to directly separate the background from the foreground without knowing the location of the characters first.

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