License Plate Localization from Vehicle Images: An Edge Based Multi-stage Approach

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Abstract- **Automatic license plate recognition (ALPR) system for vehicles is a challenging area of research due to its importance to a wide range of commercial applications. The first and the most important stage for any ALPR system is the localization of the license plate within the image captured by a camera. Variety of techniques has already been reported for localization of license plate and recognition of license number thereafter. But most of the works seem to be applicable for a very controlled environment. In the current work, we have concentrated on localization of license plate regions from true color still snapshots captured in a very realistic situation. The technique is based on a novel multi-stage approach for analysis of vertical edge gradients from contrast stretched gray-scale images. The technique successfully localizes the actual license plates in 89.2% images.**

Index terms- **median filtering, histogram equalization, Sobel's vertical edge, mean, standard deviation, area, aspect ratio**

I. INTRODUCTION

Localization of potential license plate regions(s) from vehicle images is a challenging task due to huge variations in size, shape, colour, texture and spatial orientations of license plate regions in such images. In general, objective of any *Automatic License Plate Recognition (ALPR)* system is to localize potential license plate region(s) from the vehicle images captured through a road-side camera and interpret them using an *Optical Character Recognition (OCR)* system to get the license number of the vehicle.

ALPR systems are widely implemented for automatic ticketing of vehicles at car parking facilities, tracking vehicles during traffic signal violations and related applications with huge saving of human energy and cost. In an online ALPR system, the localization and interpretation of license plates take place instantaneously from the incoming still frames, enabling real-time tracking of moving vehicles through the surveillance camera. An offline ALPR system, in contrast, captures the vehicle images and stores them in a centralized data server for further processing, i.e. for interpretation of vehicle license plates. The current work, discussed in this paper, comes under the later category of solutions.

Various techniques have been developed recently for the purpose for efficient detection of license plate regions from offline vehicular images. In general, most of the works on ALPR systems [1-4] apply edge based features for localizing standardized license plate regions. Some of these works [2, 5, 6] captures the image of a vehicle carefully placed in front of a camera occupying the full view of it and taking a clear image of the license plate. But in an unconstrained outdoor environment there may be huge variations in lighting conditions/ wind speed/ pollution levels/ motion etc. that makes localization of true license plate regions even more difficult.

Moreover in the practical scenario there may be multiple vehicles of different types in a single scene along with partial occlusions of the vehicles and also the license plates from other objects, where the above methods do not work. In one of the earlier works [1], Rank filter is used for localization of license plate regions giving unsatisfactory result for skewed license plates. An analysis of Swedish license plate is done in [2] using vertical edge detection followed by binarization. This does not give better result for non-uniformly illuminated plates. During the localization phase the position of the characters is used in [3]. It assumes that no significant edge lies near the license plate and characters are disjoint. In Greece the license plate uses shining plate. The bright white background is used as a characteristic for license plate in [4]. A work on localization of Iranian license plate is done in [5]. In [6], W. Jia used mean shift algorithm for localization of license plate giving satisfactory result for license plates having color different from the body color. Spanish license plate is recognized in [7] using Sobel edge detection operator. It also uses the aspect ratio and distance of the plate from the center of the image as characteristics. But it is constrained for single line license plates. An exhaustive study of plate recognition is done in [8] for different European countries.

In the developed countries and in most of the developing countries the attributes of the license plates are strictly maintained. For example, the size of the plate, color of the plate, font face/ size/ color of each character, spacing between subsequent characters, the number of lines in the license plate, script etc. are maintained very specifically. Some of the images of standard license plates, used in developed countries, are shown in Fig 1 (a). However, in India, the license plates are not yet standardized across different states, making localization and subsequent recognition of license plates extremely difficult. Moreover, in India license plates are often written in

Figure 1. License Plate images.
(a) Standardized license plates of European vehicles
(b) License plates of Indian vehicles

multiple scripts. Fig. 1(b) shows some of the typical Indian license plates with variety of shape, size, script etc. This large diversity in the features of the license plate makes its localization a challenging problem for the research community.

Two types of license plates are used in India for two categories of vehicles. For commercial vehicles, the license plate has a yellow background and black scripts on it. For private vehicles a white background with black script is used. The current Indian vehicle registration scheme comprises of a two-letter identification code for the state, in which the vehicle is registered. It is followed by a two-digit numeric code to identify the district. In the union territories and the erstwhile union territory of Delhi, the district code is omitted. This is often followed by a series code, e.g. 2M is the second series for motorbikes and. 14C is the fourteenth series for private cars. Recently many states have been adapting the dual letter series code system, for example car series' are CA, CB, CC; motorbike series' are MA, MB and so on. Finally a four-digit number is used to uniquely identify the vehicle. Most states however still use the standard series code, denoted by a single letter of the alphabet. When the alphabet reaches Z, the length of the prefix is increased to 2. So after WB-02 9999, the next number is WB-02 A 0001 and after WB-02 Z 9999 it is WB-02 AA 0001 and so on.

Unfortunately, limited works [9-10] have been done on detecting the license plates from Indian vehicles. In the light of above facts, the objective of the paper is to present a robust technique for localization of license plate regions from Indian vehicle images, an important step towards development of a complete ALPR system.

II. COLLECTION OF THE DATASET

The dataset for the current experiment is collected as a part of a demonstration project on *Automated Red Light Violation Detection* system for a Government traffic monitoring authority of a major metro city in India. Three surveillance cameras were installed at an important road crossing in Kolkata at a height of around ten meters from the road surface. All the surveillance cameras were synchronized with the traffic signaling system such that the camera captures the still snapshots only when the traffic signal is turned *RED*. All the cameras were focused on the *Stop-Line* to capture frontal images of vehicles near the *Stop-Line* on a *RED* traffic signal.

The complete image dataset comprises of more than 15,000 surveillance still snapshots, captured over several days/nights in an unconstrained environment with varying outdoor lighting conditions, pollution levels, wind turbulences and vibrations of the camera. 24-bit color bitmap images were captured through CCD cameras with a frame rate of 25 fps and resolution of 704 x 576 pixels. Not all these still snapshots contain vehicle images with a clear view of license plate regions. For the current experiment, we have identified 500 images that contain complete license plate regions appearing in different orientations in the image frame.

III. PREPROCESSING TECHNIQUES

As described in previous section, true color still snapshots of resolution 704×576 pixels were captured through multiple surveillance cameras over day and night with embedded noise and huge variations in image quality. Following preprocessing techniques are implemented in the current work to address the issues mentioned above. Fig. 2(a) shows a sample still snapshot and the corresponding result after preprocessing techniques (as discussed in section 3.1. to 3.3.) applied on it are shown in Fig. 2(b-c).

A.. Gray scale conversion

From the 24-bit color value of each pixel *(i,j)* the R, G and B components are separated and the 8-bit gray value is calculated using the formula:

$$gray(i, j) = 0.59 * R(i, j) + 0.30 * G(i, j) + 0.11 * B(i, j) \quad (1)$$

B. Median filtering

Median filter is a non-linear filter, which replaces the gray value of a pixel by the median of the gray values of its neighbors. We have used 3×3 masks to get eight neighbors of a pixel and their corresponding gray values. This operation removes salt-and-peeper noise from the image.

C. Contrast enhancement

Contrast of each image is enhanced through histogram equalization technique, as discussed in [11]. Total 256 numbers of gray levels (from 0 to 255) are used for stretching the contrast. Let total number of pixels in the image be *N* and the number of pixels having gray level *k* be n_k. Then the probability of occurrence of gray level k is, $P_k = n_k / N$. The stretched gray level S_k is calculated using the cumulative frequency of occurrence of the gray level *k* in the original image using the formula:

$$S_k = \sum_{j=0}^{k} \frac{n_j}{N} \times 255 \quad (2)$$

where, 255 indicates the maximum gray level in the enhanced image.

IV. EDGE DETECTION

In this work, we have extracted the edges created by the characters within the license plate. *Sobel* edge operator [11] is used for detection of edge gradients. It is seen that when the characters of the license number are

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written horizontally the vertical edges of each character appear at regular interval and they have a specific height. The pattern and concentration of the vertical edges also remains in conformity with the pattern of the license number. This appearance of vertical edge pattern is statistically seen to occur within the license plate, no where else within the natural scene of the image. In the present work, we have explored this phenomenon to find the license plate region within the image. The vertical edge at point *(x,y)* is found using the following formula:

$$gradV \ (y,x) = \sqrt{\left(\sum_{m=-1}^{+1} \sum_{n=-1}^{+1} V\_mask \ (n,m) \ img\_contrast \ (y+n, x+m)/4 \right)^2}$$

(3)

where, *img_contrast* is the enhanced image over which the edge detection algorithm is operated upon, *V_mask* is the *Sobel's* mask for vertical edge detection as given below and *gradV* is the vertical edge gradient.

$$V\_mask = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

(4)

Depending on the value of the *gradV* we have binarized the edge image using the threshold μ_{gradV} (mean edge gradient value) and formed the edge image *img_edge*. Fig. 2(d) shows the result of edge detection after binarization is applied on it.

Figure 2. Preprocessing tasks on a sample image
(a) A sample true color vehicle image
(b) Gray level equivalent of the input image
(c) Contrast stretched gray level image
(d) Significant vertical edge gradients of fig. 2(c)

Deciding the threshold value for binarization of edges is a key factor. In the current work we have generated a dataset of numerous license plates only and extensively applied the binarization method over them for different values of threshold as seen from the histogram of the images of the license plate.

V. LICENSE PLATE LOCALIZATION

In the present work, we have developed a novel approach based on prominent vertical edges computed from vehicle images for localization of significant license plate regions. It may be observed from Fig. 2d, that the pattern of the vertical edges at the license plate region is very dense and prominent. Also, the vertical run-lengths of edge pixels within the license plate regions are almost equal to the height of the characters therein.

Using the aforesaid attributes, the overall localization algorithm may be subdivided into the following intermediate stages, *viz.*, identification of potential band of rows, primary localization of license plate regions based on statistical distribution of vertical edge pixels, refinement of license plate regions based on prominent vertical edges and finally, localization of license plate bounding box by removing the noise segments. The steps are discussed hereunder in an algorithmic approach.

First Stage:

1. *For row=1 to height*
    For col= 1 to width
        edgepixel[row]=edgepixel[row]+edge(row,col)

2. *For row=1 to height*
    If edgepixel[row]>T_min
        mean[row]=mean(); //of edge pixel positions
        variance[row]=variance( ) //of edge pixel positions

3. *For row=1 to height*
    Find the set of continuous rows satisfying
    variance[row]> maximum variance (V_xmax).
    //This set actually gives the probable n bands having
    //license plates (bounded by black lines, as shown in
    //Fig.3(a).

4. *For each band,*
    set top= starting row
    set bottom= ending row.

The value of T_{min} and V_{max} are calculated from the generated dataset.

Second Stage:

1. *For each band,*
    calculate minimum and maximum values of μ_x (μ_{xmin}
    and μ_{xmax})
    calculate maximum value of v_x (v_{xmax}).

2. *For each band,*
    set left= (μ_{xmin} - v_{xmax})
    set right= (μ_{xmax} + v_{xmax}).

3. *For each band,*
    Draw box having diagonal corners (left, top) and
    (right, bottom)
    //This box will localize the position of license plate
    ///(bounded by black box in Fig.3(b)

Upto this point what we get is the statistically obtained potential license plate region whose dimension indicates the maximum area in which the license plate can appear.

Third Stage:

1. *For each bounding box in second stage,*

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From left to right
   find first prominent vertical edge having
   height > predefined minimum height (H_{min})
   if found, set new_left=left
From right to left
   find first prominent vertical edge having
   height > predefined minimum height (H_{min})
   if found, set new_right=right

2. *Draw box with left-top and right-bottom corners' coordinates as (new_left, top) and (new_right, bottom) //(bounded by black box in Fig.3(c).*

3. *Among these new bounding boxes, the overlapped or very close bounding boxes are merged to get common bounding box. This case actually occurs in case of multi line character set license plate.*

The value of H_{min} is actually dependent on the height of the characters in the character set and is obtained by averaging the heights of the vertical edges within the bounding box obtained in second stage. The outcome of this stage is the true license plates and along with them there may be additionally generated boxes indicating false license plates. These noisy boxes are removed in the fourth stage depending on the aspect ratio and the area of the generated boxes.

Fourth Stage:

1. *For each bounding box in third stage,*
     aspect_ratio=box_width/box_height
     area=box_width×box_height.

2. *Among all bounding boxes,*
     noise boxes are removed by allowing boxes having specific range of aspect ratio and area
   //(final selected license plate region bounded by black //box in Fig.3(d).

The average value of aspect ratio and the area are calculated from the generated dataset for single-line and multiline character set license plates separately.

VI. EXPERIMENTAL RESULTS

As discussed in section 500 number of true color images of resolution 704×576 pixels were selected for preparation of data set. The experimental threshold values are statistically computed from the image data sets and are obtained as mentioned below:

- *Minimum number of edge pixels in a row, $T_{min}=5$.*
- *Maximum allowable variance of the position of the edge pixels in a row containing license plate, $V_{max}=40$.*
- *Minimum height of the selected band of rows containing license plate, $H_{min}=5$.*

(a)   (b)

(c)   (d)
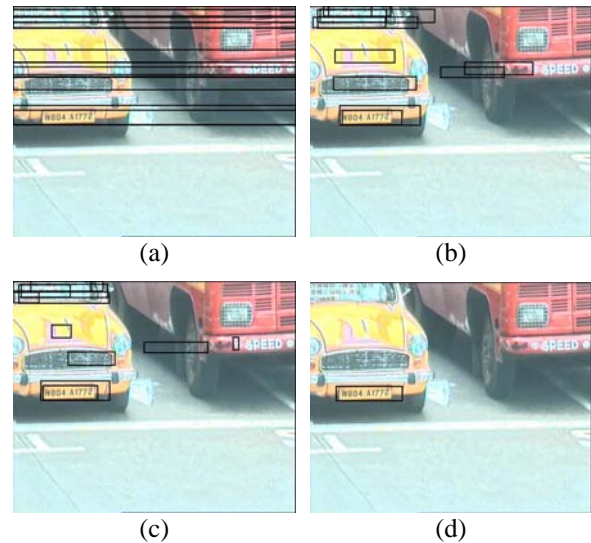
Figure 3. Different stages of license plate localization
(a) Selected rows after stage 1
**(b) Potential license plate regions after stage 2**
(c) Refined license plate regions after stage 3
(d) Final license plate region(s) identified by stage 4

- *The maximum number of pixels allowed between two successive edges within the character set is considered at most $2H_{min}$.*
- *Total area of the license plate is considered to be 3000 to 6000 pixels.*
- *Aspect ratio of the license plate is considered as 1 to 2 for multi line character set and between 3 and 6.5 for single line character set.*

Using the above considerations, experiments are conducted with 500 images. Fig. 3(a-d) shows the intermediate results of the license plate localization part of experiment when done on Fig. 2a. Fig. 4(a-d) shows some of the cases where perfect localization of license plate is done, the license plate region being marked by the thick black box. Fig. 5a shows the case where license plate is wrongly localized and Fig. 5b shows the case where no license plate is detected by our program.

The result can be analyzed by considering three different cases of finding the proper license plate. We consider the result to be *false negative* if true license plate is not found and/ or false locations are detected as license plate. *False positive* cases are those where the true license plate is found and along with that other false locations are also detected as license plate. Finally, *true positive* cases are those where only true license plate is detected as a license plate. It is observed from the experimentation on the collected dataset of vehicle images that the *false negative* rate is only 8%, *false positive* rate is only 2.8% and the *true positive* accuracy is 89.2%. If the *false negative* cases only are considered as wrong cases then the combined *positive* accuracy may be estimated as 92%, where the technique localizes the true license plates from vehicle images.

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(a)　　　　　　　　(b)

(c)　　　　　　　　(d)
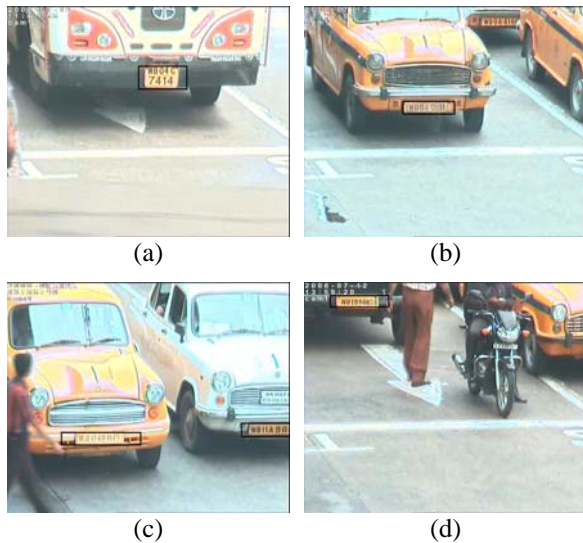
Figure 4(a-d). Sample images with successfully localized license plate regions.

(a)　　　　　　　　(b)

Figure 5(a-b). Sample images where the current technique fails to localize true license plate regions.

The technique can further be enhanced by applying some soft computing techniques for training the patterns of edge gradients. The localized license plate regions are to be subsequently processed by an effective *OCR* module for extraction of vehicle registration numbers.

CONCLUSION

In our present work, we have developed an effective method for localization of license plate regions from video snapshots of registered vehicles. The technique is extensively tested with 500 image samples and the gives satisfactory performance. One advantage of considering only vertical edges is due to fact that, the transverse motion of any car over the road makes some angle with the direction of the camera. This makes the vertical edges remain vertical but the other edges become skewed. This has made us running the same algorithm for the vehicles for which the frontal plane is inclined with the projection of the camera face to the vertical plane to the road.

As the technique is edge based, the main limitation of our algorithm is that it performs well for less noisy images and having well printed characters over the license plates. That is why we have done some preprocessing task separately on some of the images.

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