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Novel Vehicle Number Plate Segmentation Technique in Indian Conditions

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Abstract

Background/Objectives:In this paper a novel number plate segmentation algorithm is proposed, which can be further exploited to do character segmentation and character recognition. **Methods/Statistical Analysis**: The scope of this research is to segment vehicle number plate from the captured vehicle image. To accomplish this task image binarization is used as it translates any color image into black and white image. The image binarization process is carried based on the statistical formula mentioned in this paper. The binarized image is further processed to remove unwanted area and exactly segment vehicle number plate. **Findings**: The algorithm provides overall accuracy of ~97.67% with the average processing time of 134ms for 250 images captured during timings in day and night. The system works well in different illumination conditions. **Conclusion/Improvements**: The overall accuracy can be further improved by modifying the parameters of image binarization process.

Keywords: Column Trimming, Image Binarization, Image Segmentation, Number Plate, Row Trimming

1. Introduction

In developing country like India, the usage of vehicle is increased day by day. This scenario can create commotion in terms of traffic control system for the transportation. Thus, intensifying use of vehicles can create certain impediments such as terror attacks, theft and in other unlawful activities. It is very difficult to monitor these activities due to lack of automation. The most probable solution for these problems is Automatic Number Plate Recognition (ANPR) or License Plate Recognition (LPR). The ANPR can be used at various domains such as automatic toll collection[1], vehicle parking system[2], traffic control systems[3,4] and other domains. The pre-requisite task of any ANPR system is to segmentation the vehicle Number Plate (NP), which will help to accomplish the other steps such as character segmentation and character recognition. These steps are well defined in[5-10]. In this paper, our work is emphasized on NP segmentation. Many researchers have worked on NP segmentation as a part of ANPR. These systems are based on different methods mainly sliding concentric window[7], configurable method[10], fuzzy based[11], cascade framework[12], Dynamic programming[13], edge based color-aided method[14]. It is also to be noted that certain systems are specific to the country so the methodologies of algorithms of NP segmentation might be different in each system. Our system is focused to segment the NP of Indian vehicles as few efforts are done for ANPR of Indian vehicles. In[15-18]researchers have tried to develop number plate segmentation algorithm in ANPR for India but these systems are not able to provide accurate result in conditions such as different illumination conditions, different size of number plates and different type of vehicles such as private vehicles, government and

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commercial vehicles. In our work, we focused on all the types of vehicles and our system gives better result in different illumination conditions.

Many researchers attempted to develop NP segmentation for the ANPR. It is mentioned in many research papers that modified Ostu's method provides adaptive threshold and produces better result in normal image. Sometimes histogram-based methods[19] can be useful to accomplish this task. But these methods cannot be used in our system because of different illumination conditions. The method proposed by[7], provide good amount of accuracy. The method is based on two sliding concentric windows which slide through the entire image to judge whether the regions between two windows is a NP region or not. The standard deviation of two windows is calculated and then if the ratio between two standard deviations is more than the threshold set by the user then the central pixel of these two windows is region is considered as NP region. As per the authors, the threshold can be selected based on the trial and error methods. Finally, they applied sauvola's[20] algorithm to binarize the NP region. Due to two sliding concentric windows, the algorithm is time-consuming process for the images having high resolution. Another sliding concentric window based method is proposed in[9]. The distance between cameras to vehicle image was from 3 meters to 7 meters. The system provides less accuracy as compared to other systems presented in this paper and our proposed system.

For the Indian NP segmentation, the author's in[15] proposed an L shaped mask which is equal to maximum possible character dimensions. The mask is scanned through the entire binary image to find out the probable character. The region is considered as part of NP if there is at least a single white pixel on the mask and there is at least a single white pixel on the immediate next row and column of the mask. The size of each character in NP region is calculated and it is discarded if it is less than half of maximum possible character size. The authors have not reported results under the different illumination

Table 1. Performance comparison of different NP segmentation algorithms

Ref	Platform and Processor	NP detection rate	Processing Time (In Sec)
7	Visual C++	96.5%	0.111
9	Pentium IV 2.4 MHz with 1024 RAM, MATLAB R2008a	82.5%	Not Reported
10	Pentium IV 3.0 GHz Processor	95.9% (Multinationals) 96.9 %(Multi Style)	Not Reported
11	TI DM642 600 MHz/32 MB RAM, C language	Not Reported	Not Reported
12	Pentium IV 3.0 GHz Processor	98.77% For 320 X 240 99.807% For 640 X 320 99.857% For 640 X 480	Not Reported
14	Pentium IV 3.0GHz processor, MATLAB 6.0	Not Reported	1.1
15	Not reported	87%	Not Reported
17	MATLAB	Not Reported	Not Reported
18	MATLAB	Not Reported	Not Reported
16	MATLAB	Not Reported	Not Reported
22	Pentium 2.66 GHz processor, MB RAM, Visual Studio 2005	98.3%	.015
23	2. GHz CPU.	94.12%	Not Reported
24	Pentium 2.8 GHz Processor	96.4%	0.204
25	Not Reported	98.45%	Not Reported
26	Not Reported	97.6%	Not Reported
27	Pentium-IV 2.26-GHz, 1 GB RAM, MATLAB	97.3%	Not Reported
28	MATLAB	Not Reported	Not Reported
29	Not Reported	Not Reported	Not Reported
30	Pentium IV 3.0 GHz processor	81.2%	0.4
31	C Programming, 2.3 GHz processor	Not Reported	0.025
32	Not Reported	92.31%	Not Reported

conditions and different font size and font type of vehicle NP. Another approach based on edge detection and morphological operations is proposed in[17]. The segmentation of NP is a four step process. In the first step, the entire image is converted to grey scale based on the formula presented in this paper. In the second step, the image is enhanced using median filtering and then Sobel operator is used to detect vertical edges. In the third step, morphological operators such as open and close are used to locate candidate regions. Finally non NP regions are removed by using horizontal and vertical crop operations. For Indian car NP recognition, authors in[18] proposed an approach based on bernsen's[21] algorithm. The authors claim that it is a novel approach based on Gaussian filter and bernsen's algorithm for effective shadow removal. The authors claim to have 14s of overall processing time including NP segmentation, character segmentation and character recognition but only NP segmentation time is not reported in this paper. Morphological operations such as dilation and erosion are applied in[16] to segment Indian vehicle NP. The more details about experiment set up and experiment results are not presented in this paper.

In ANPR high accuracy is the key issue. To achieve high accuracy, author's in[12] proposed cascade framework for statistical plate recognition. They consider different variation conditions such as plate location, quantity (for 0 or more plates), plate size, color of plate and other objects such as screw and frames. The algorithm works well in various illumination conditions.

To detect multinational style NP[22] proposed gradient based strategy. In this method the image is processed to localize areas with a high vertical gradient density. After a pre-processing step such as contour enhancement, vertical Sobel mask filter is applied then gradient accumulation approach is applied which is inspired from[33]. To binarize the plate authors used local version of fisher/Otsu's binarization[34]. Another multi-style NP detection system based on configurable framework is depicted in[10]. The authors consider different parameters such as plate rotation angle, plate line number, character type and format to consider segmentation of NP. The authors mention that number of lines, character types and format are considered as internal factors and illumination, rotation angle, LP size and location in an image are considered as external factors. All these factors are considered in the configurable framework. As per the authors, number of lines, character types and formats are three most important internal elements and rotation angle is the most important external element. So they consider only these elements as part of their algorithm as they claim that illumination, NP size are covered in existing ANPR (LPR) system. The authors in[29,30] also presented the algorithm to detect multinational NPs.

Edge and region based method is applied to detect NP in[23]. In this paper authors propose new filtering method known as "region" based method to smooth the image to smooth and uniform the background area of image. First, the image is enhanced by using intensity variance and edge density. Then it is filtered based on the modified region based method by using Gaussian filter K of 13 X 13 and the weight r which is calculated based on the formula given in this paper. Finally, the NP is detected based on vertical edge detection, morphological filtering and geometric features. In vertical edge detection Sobel operator is used, while open and close operator are used in morphological filtering and area (size of region), aspect ratio and edge density are considered as geometric features. This method is applicable to detect Iranian NPs and authors claim that it can be applicable to detect NPs for foreign countries. Similar approach is proposed in[24]. Another edge based method is proposed in[14]. The authors proposed edged based and intensity based approach to segment the NP in from the lower quality images. The contrast is increased in NP like regions to avoid the missing possible NP regions. Furthermore, a match filter is developed for detection of NP region. This filter models the vertical edge density of plate region regarding its neighborhood. The authors emphasize that colored texture in the plate can be used as a cue for plate detection. Finally, Multimodal Neighborhood Signature (MNS) method is applied to characterize the color information in plate. Canny edge detection based algorithm is presented in[25].

The modified bernsen's algorithm based on the min and max color value of particular window in applied in[35]. To remove shadow from the NP the authors applied Gaussian filter based mask to filter the image. The Gaussian filter is applied to the original image to obtain the new filtered image. The average value of min and max colors is calculated from the filter image to find the threshold. They applied the parameter α to adjust the balance between traditional bernsen's algorithm and their algorithm. The parameter β is applied to adjust different between current pixel value and threshold. The authors suggest value of β as 0.9 for the optimal result. The algorithm work well in different illumination conditions but calculation of Gaussian filter and generating filtered image might be time consuming for the images having high resolution.

Feature salient based method is proposed in[27]. In this paper, the authors applied prior probability based model to separate target (NP) from the background. As per the authors comparing with the other features (such as length, width, and area) of a vehicle plate, shape features, texture features, and color features have more salient effect. Therefore, they mainly analyzed these three features and computed their salience. They applied Hough transform to detect horizontal and vertical edges for detection of rectangular area of vehicle NP. Similar approach is presented in[31]. For CCTV forensic applications they proposed a novel approach for efficient localization of license plates. The rectangle region is selected based on size and aspect ratio of the images. Finally, Histogram of Gaussian (HOG) and nearest mean classifier is applied to detect NP. These algorithms might not produce good results with the images having non-rectangular NPs or no rectangles.

Color based methods are propose in[11,28]. In[11] authors presented algorithm based on fuzzy logic. For feature extraction Hue, Saturation and Value (HSV) is applied. The fuzzy classification function for color recognition is described by the fusion of three weighted membership degrees. They also applied a learning algorithm to obtain the correlative parameters. The authors claim to have better results in the images having no fixed location of vehicle NP. In[28] only color characteristics are applied to detect NPs. Further technical details regarding the NP segmentation algorithm are not presented in this paper. The algorithm might not be suitable in different illumination conditions.

The comparison of NP segmentation part of different ANPR systems is presented in Table 1. In some systems overall accuracy of ANPR is reported but accuracy of NP segmentation only is not presented so we have not included the accuracy data of these systems in Table 1. It also to be noted that in some systems processing time of ANPR is mentioned but processing time of NP segmentation only is not presented so we have not included processing time of these systems.

2. Design of System

The block diagram of the system is mentioned in the Figure 1. As per the Figure 1, first step is to binarize the image, which is based on the adaptive threshold for different local windows. This step is well explained in section 2.1. In section 2.2, row trimming section is explained to remove non NP regions from the horizontal direction while vertical non NP regions are removed in section 2.3.

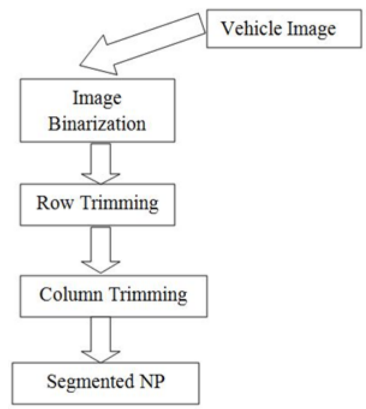

Figure 1. Architecture of the system.

2.1 Image Binarization

Image binarization is the process of converting any image to the black and white based on the threshold. It plays vital role in NP segmentation as it separates the NP background and NP region. The equivalent pixel intensity values 0 and 255 represent black and white color respectively in RGB (Red, Green, and Blue) color model. In this method we used RGB color model. The Indian NP is mainly of three types:

- Private vehicle NP
- Government Vehicle
- Commercial Vehicle

In Figure 2(a) and Figure 2(b) image of private vehicle NP is shown. In India, Road and Transport Office (RTO) is the authority to issue the vehicle number to the vehicles. Before few years, the vehicle owners were given choice to get vehicle number printed on NP in any format or font size. So the vehicles registered before few years are having non-uniform NPs, one of the examples is shown in Figure 2(b). The vehicles registered in recent years, RTO issues the NPs with vehicle number printed on it which is shown in Figure 2(a), so all these vehicles are having uninform number plate in terms of font type and font size. So the biggest challenge is to segment different NPs having user printed NPs (non-uniform) and RTO printed NPs (uniform). Each private NPs have white color as background and black colors as vehicle number. The commercial vehicle NPs have yellow color as background and black color as vehicle number, which is shown in Figure 2(c). So it is a challenging task for the binarization process to segment the NP of Indian vehicle. In[36] Yoon mentions a very good comparison study of different binarization methods. It is not easy to judge any one method as the best method as NP segmentation is dependent on four parameters such as plate rotation angel, character line number, recognition modeland character formats[5]. Apart from these parameters, external factors like uneven illumination condition and un-uniform character formats for old NP (before few years) also make segmentation task more difficult. After studying different image binarization methods in above sections, we designed the novel image binarization algorithm, which is discussed in this section.

The biggest challenging task of any image binarization process is to select the threshold. In our method, a scanning window of m X n scans the entire image from left to right and top to bottom. The threshold T is calculated based on the following formula:

$$T = \mu_{(x,y)} + \left(\frac{\max}{100 - \frac{\delta}{k1}}\right) * \alpha * \beta * k2 \quad x, y \in (m,n) \qquad (1)$$

Here, max = maximum intensity value of all pixels in window m X n between 0 to 255.

$$\alpha = e^{-\left(\frac{1}{\delta}\right)} \text{ where } \delta = \text{standard deviation of window m X n} \qquad (2)$$

$$\beta = e^{-\left(\frac{1}{\theta}\right)} \text{where } \theta = \delta\,(\mu_{(x,y)}, \mu_{mincolor}) \qquad (3)$$

In our experiment, we chose m as 13 and n as 37 which is chosen based on trial and error method. The variable μ is mean values of median and mean of the window m X n which is mentioned in equation (1). It is observed that all the NP characters are having color values less than or near to μ. But some of the non NP regions are also having similar characteristics, so we need to classify these regions as non NP. It is also perceived that the NP regions are having higher standard deviation than the non NP regions due to the difference between LP characters and background. So standard deviation δ is calculated for the window m X n and it is used in the equation (2). As per equation (2), higher value of δ (NP regions) decreases value of α slightly, while lower value of δ (non NP regions) decreases value α of considerably. The value of θ is calculated based on the extensive experiments and trial and error methods. In our experiments, we observed that the lower value of standard deviation between $\mu_{(x,y)}$ and $\mu_{mincolor}$ is the probable non NP area. High value of θ decreases values of β slightly and low value of θ decreases value of β considerably. The value of $\mu_{mincolor}$ can be obtained by calculating mean of intensity of all the pixels having value less than $\mu_{(x,y)}$ for the window m X n. As per the equation (1), higher values α and β indicate that the region is NP and Threshold T is decreased slightly and lower values of α and β indicate that region is non NP having considerable decrease in the threshold T. The value of k is considered as parameter to remove the unwanted noise in the image. In this system, k1 and k2 are the parameters used for effectively removing shadow. The value of k1 is set as 6 and k2 is set as 1 for the better result in the system. Finally, the image is binarized according to the equation (4):

$$g(x,y) = \begin{cases} 0, if \;\; f(x,y) < T \\ 255, otherwise \end{cases} x, y \in (m,n) \qquad (4)$$

After the image is binarized, it is advanced to the next step for removing non NP regions from horizontal direction.

2.2 Row Trimming

(a) (b) (c)

Figure 2. Different types of Indian NPs.

As per the Figure1, to remove the unwanted region from vehicle image from horizontal direction, row trimming step is carried out. In this method, the image is divided in the row clusters each of size N. Then the entire image is scanned from top to bottom cluster wise. For each cluster, percentage of black and white pixel is calculated. Initially, the first cluster is added to the list of possible clusters. If percentage of black pixel is less or equal to than M1 or percentage of white pixel is less or equal to M2, the

Table 2. Row Trimming Algorithm

```
Step 1: The input image is binarized image g(x, y).
Step 2: Perform region clustering based on row
        rowcluster=0
        N=10 {N=number of clusters}
         while(rowcluster <height of image)
              for i=rowcluster to rowcluster +N
                  for j=0 to width of g(x,y)
                    /*calculate the amount of black color and white color to find the percentage of
                      respective colors  at the end of loop */
                   end for
                   black_per=percentage of black pixels in the cluster
                   white_per=percentage of white pixels in the cluster
              end for
             if (black_per<=M1 OR white_per<=M2)
                 /* store the ith cluster in the possible clusters list */
                 clusters.Add(i)
                end if
                  rowcluster = rowcluster +N;
           end While
          /*Remove clusters for multicolumn NP problem */
         foreach cluster in clusters
               diff1=absolute difference between cluster, cluster -1
               diff2=absolute difference between cluster, cluster +1
              if(diff1!=N && diff2!=N && diff1!=diff2)
              {
                 /*remove the cluster from the list of clusters*/
                  Clusters.remove(cluster)
              }

         end for
Step 3: Find the start row and end row
        foreach cluster in clusters
            diff=difference between cluster and cluster +1
             if(diff is maximum)  {                  startrow=cluster
                   endrow=cluster +1
            }
        end for
{ N,M1 and M2 can be calculated based on trial and error. In our experiment M1 =3% and M2=3% for image having very less
  number of black colors, M1=2% , M2=% for image having negligible amount of black colors and M1=11%, M2=11% for image
having significant amount of black colors. Value of N is
  taken as 10
}
```

Table 3. Column Trimming Algorithm

```
Step 1:The input image is binarized image g(x, y).
Step 2: Perform region clustering based on column
        rowcluster=0
        N=20 {N=number of clusters}
        while(colcluster <width of image)
              for i=rowcluster to rowcluster +N
                   for j=0 to Height of g(x,y)
                     /*calculate the amount of black color and white color to find the percentage of respective colors
                       at the end of loop */
                   end for
                   black_per=percentage of black pixels in the cluster
                   white_per=percentage of white pixels in the cluster
              end for
             if (black_per<=M1 OR white_per<=M2)
                 /* store the ith cluster in the possible clusters list */
                 clusters.Add(i)
                end if
                  colcluster = colcluster +N;
           end While
Step 3: Find the start column and end column
        foreach cluster in clusters
            diff=difference between cluster and cluster +1
           if(diff is maximum)
           {
                  startcol=cluster
                  endcol=cluster +1


            }
        end for
Step 4: /*Remove clusters for gaps problem of NP characters */
while (endrow < cluster.count)
{
   If(cluster[i+1]-cluster[i]==N)
     Exit the while loop
}
If(endcol < cluster.count)
  endcol=cluster[i]
{
 N,M1 and M2 can be calculated based on trial and error. In our experiment M1 =5% and M2=5% for. Value of N is
 taken as 20
}
```

Table 4. NP Segmentation experiment set up details

Sample Set	Number of images	Image size	Accuracy	Processing Time(in ms)
Vehicle images captured during 9:00 am to 4:30 pm	150	800 X 600, 640 X 480	~99.33%	134.5
Vehicle images captured after 4:30 pm	100	800 X 600, 640 X 480	~96%	133.5

Overall Accuracy = ~97.67%

cluster is added in the list of possible clusters. The entire process is carried out for all the clusters. The maximum difference between two adjacent clusters indicates that the region between two clusters is a NP region. For NPs having multiple rows (5),(10)itdoes not always produces correct result because of the gap between first line and second line of the NP characters as shown in the Figure 3. As shown in Figure 3, due to the gap between line 1 and line 2 the distance between cluster 1-cluster 2 and cluster 2-cluster 3 is same. So the algorithm can consider cluster 1 as starting row and cluster 2 as ending row and only line 1 is considered as part of NP, the region in the line 2 is not considered as part of NP. To overcome this problem, the ith cluster is removed from the possible clusters list if absolute difference between clusters i-1, i and clusters i, i+1 is not equal to cluster size n and both differences are not equal. After removing the unnecessary clusters from the list of clusters, the difference between two adjacent clusters is calculated to judge the starting row and ending row of the NP. The adjacent clusters having largest difference are considered as start row (ith cluster) and end row((i+1)th cluster). For our experiments the value of row cluster n is selected as 10. The algorithm is well explained in Table 2.

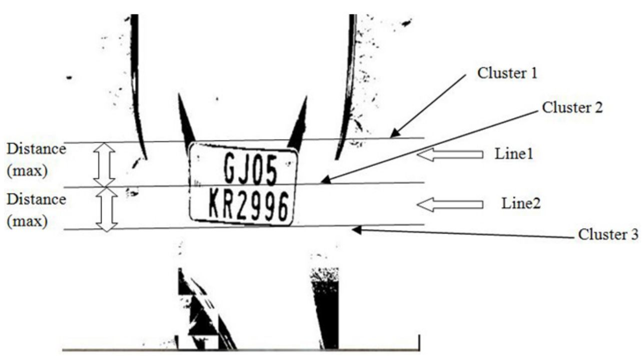

Figure 3. Binarized number plate with multiple rows.

2.3 Column Trimming

This step is carried out to remove non NP area from the vertical direction in the vehicle image. The image is divided in N clusters and then the entire image is scanned from left to right. For each cluster, percentage of black and white pixel is calculated. Initially, the first cluster is added to the list of possible clusters. If percentage of black pixel is less or equal to than M1 or percentage of white pixel is less or equal to M2, the cluster is added in the list of possible clusters. The entire process is carried out for all the clusters. The maximum difference between two adjacent clusters indicates that the region between two (ith cluster and (i+1)th cluster) clusters is a NP region. These steps are not enough for NPs having little more gaps between characters and column clusters might not be identified properly. To overcome this problem, we scan all the clusters from (i+1)th cluster to all the clusters until we find the different between two adjacent cluster is equal to cluster size N. This process is explained in Table 3.

3. Experiment Results

This algorithm presented in this paper works in 24 X 7 manners. All the test images are captured during different time at various areas across the city. The test set 1 contains 150 images captured during the hours 9:00A.M to 4:30P.M and sample set 2 contains 100 image captured during the hours 4:30P.M to 12:00A.M. We achieved accuracy of sample set 1 by 99.33 % and sample set 2 by 96%. The overall accuracy of the algorithm is ~97.67%. The overall processing time is ~134 ms which fulfills real time requirement. The System is developed using Intel core i3 2.13 GHz processor having 3.0 GB RAM. The details of this experiment setup are mentioned in Table 4. Few of the test images from the exhaustive set of 250 images with the successful segmentation result are shown in Figure 4.

4. Conclusion and Future Work

The proposed NP segmentation algorithm gives better accuracy for Indian vehicles. It provides better accuracy in the different illumination conditions such as brightness, darkness and image shadow. Example of image with shadow is shown in seventh image of Figure 4 (a) and Figure 4 (b). This algorithm may not work properly for old Indian vehicles, since they are not having any fixed format or size of the fonts in number plates.

(a) (b)

Figure 4. (a).NPs before segmentation (b).NPs after successful segmentation.

(a) (b)

Figure 5. (a).NP before segmentation (b).NP after segmentation failure.

There are certain images on which the algorithm does not work effectively. Such complex image is shown in the Figure 5(a) and the image after binarization is shown in Figure 5(b) which is not successfully binarized. The probable causes of this failure are light emitting from the capturing device, non-uniform NP characters and very bad illumination conditions.

The processing time can be further improved by resizing the images to the smaller size than 800 X 600 or 640 X 480. The optimized code can also improve the accuracy as our present code is not optimized. We achieve this accuracy by capturing the images at the distance of around 5 to 10 meters from camera and vehicle. Furthermore, the pixel resolution of camera was 5 mega pixels so our system might not work well if camera resolution is less than 5 mega pixel and distance is greater than 10 meters. So our future work is to improve the accuracy in these conditions.

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