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REAL TIME INDIAN VEHICLE LICENSE PLATE LOCALIZATION

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ABSTRACT

Localization locates the region of License Plate (LP) in a vehicle. This region is also denoted as a license plate candidate. Localization is the most important step in license plate recognition. It is complex and requires lots of data to train and to draw the Bounding box. Before going for localization it is mandatory to get the boundary of the LP. The existing localization is not efficient in real time due to environment noise. To overcome this problem, this paper proposes an Anisotropic Gaussian with OTSU and Blackhat (AGOB) algorithm based license plate localization. Otsu not only deals with the gray scale, but also works with spatial information of real time shape measures. Otsu thresholding with Gaussian is the best combination for locating the Required Region of Interest (RROI) in real time under varying illumination condition. The efficiency of license plate detection is calculated using the parameter LDR (License plate Detection Rate) and the proposed method found to give better LDR than the existing schemes.

KEYWORDS: Bounding Box, Blackhat Transformation, Real Time License Plate Detection, Localization

Indian Car License Plate Recognition (ICLPR) system recognizes the Alphanumeric character from the License Plate (LP) for the purpose of retrieving the vehicle owner's information. The License platr information is used to monitor and control the access of a vehicle in toll gate, automatic gate open of known authorized vehicle, law enforcement, parking, etc [Paul et. al., 2005]. Generally recognizing of character in LP involves four main processes namely, Plate Detection and Extraction, Localization, Character Segmentation and Character Recognition [Tian et al., 2015]. Extracting and isolating the License Plate Candidate region is an important stage for recognizing the character of License plate.

In real time, the images are blurred, corrupted by noise, less clarity due to illumination variation, shadow and contrast. Hence LP detection process is not very efficient. To overcome this problem, filters are used and they carry out smoothing, sharpening and enhancement [https://www.cs.auckland.ac.nz/courses/compsci]. Edge detection has to be accurate inspite of ambiguity and quality of irregularities in locating the RROI [Paul et. al., 2005].

Figure 1 shows the procedural diagram for recognizing the License plate character of ICLPR. There are some of the real time environmental factors to be considered in locating the License Plate candidate. They are shown in Figure 2.

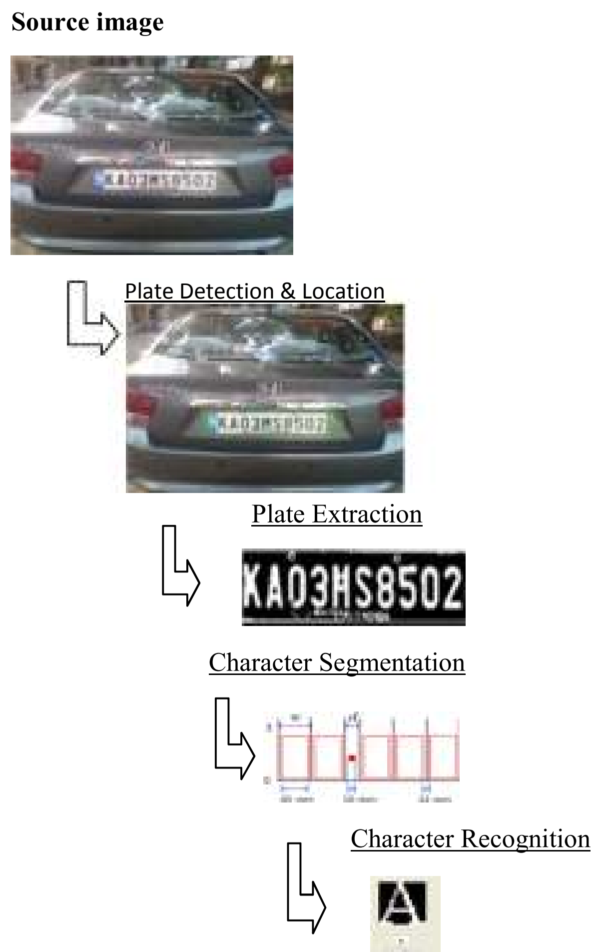

Figure 1: General flow diagram for character recognition

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Organization of the paper

The grail of this paper is to propose an enhanced edge detection method based on filtering and thresholding using Gaussian and Otsu respectively followed by a transformation method called as blackhat operation. The paper is presented in five sections. In section I, a brief study is made about edge detection methods. Section II explains the steps involved in locating the License Plate. In the third section, this paper presents the proposed AGOB method. Section IV presents the implementation and statistical result analysis. Section five presents the conclusion.

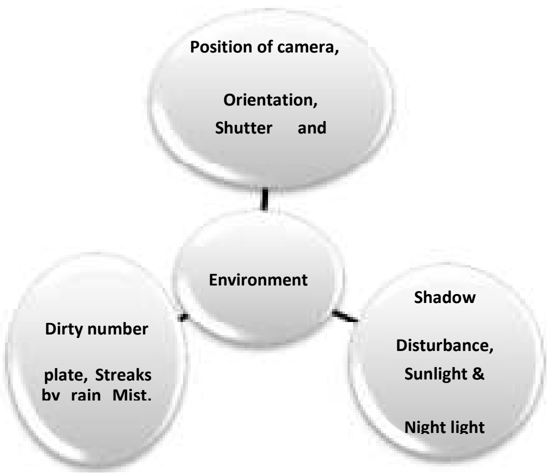


Figure 2: Real Time Environment factors

Literature survey

Locating the license plate region with a low resolution is a topic of research [Dun et. al., 2015] [Li et. al., 2013] [Deb et. al., 2009]. Detecting the license plate needs to be improved further for complex background. The combination of Edge detection and Morphological operation is an efficient method for locating and extracting the license plate [Paulo et. al., 2010]. Top hat transformation performs the removal of required objects and also smoothes the edges of the source image [Gou et. al., 2016].

LOCALIZATION

Localization is the most important stage for extracting the license plate [Anagnostopoulos, 2014]. It is substantially complex and requires a lot of data to train the bounding box. This step is carried out using morphological operation using blackhat for revealing the dark region against the background. After finding the contour in the threshold image, the aspect ratio, i.e. four coordinate points are found for computing the bounding box such as height, width, x, y in order to locate the plate region. After detecting the License plate, perspective transformation is carried out for further processing.

Figure 3: Bounding box

Figure 3 shows the bounding box of Required Candidate Region (RCR). The flow chart of Localization is shown in Figure 4.

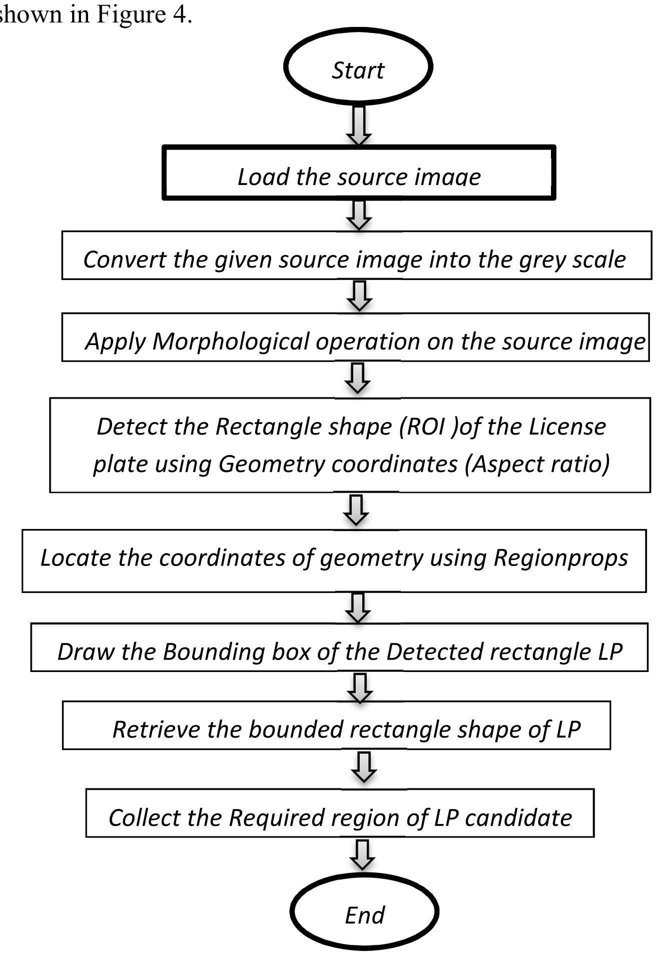


Figure 4: Flow chart for Drawing and Retrieving the bounded LP candidate

Geometric Co-ordinates for Drawing the Bounding Box

The Bounding box is a four element position vector which indicates the size and position for cropping the RCR. The required geometric co-ordinates for drawing the bounding box of License plate are x, y, height and width.

$$(x_{min}\ y_{min}\ x_{max}\ y_{max}\ height, width) \qquad (1)$$

Consider b, as a bounding box , it is analytically derived as follows:

Given point b,

$(\boldsymbol{b} = \boldsymbol{b_i}\,(\boldsymbol{x_i}, \boldsymbol{y_i}))\ \boldsymbol{where}\ \boldsymbol{i} = \mathbf{1} \ldots \ldots \boldsymbol{n}.$

$(x_{min} = min_{i=1\ldots n}\, x_i)$

$(x_{max} = max_{i=1\ldots n}\, x_i)$

$(y_{min} = min_{i=1\ldots n}\, y_i)$

$(y_{max} = max_{i=1\ldots n}\, y_i) \qquad (2)$

Figure 5: Cropped region

The bounding box is constructed using above mentioned four parameters and Fig 5 shows the cropped real time Indian License plate region.

PROPOSED AGOB Enhanced hybrid scheme for Localization

The proposed Anisotropic Gaussian with Otsu and Blackhat Algorithm (AGOB) is the combination of edge detection along with morphological operation. The accuracy of scissoring the real time candidate region is increased in the propsed method. It is carried out using the Python [https://wiki.python.org/moin/BeginnersGuide]. This proposed method is a hybrid of three process, namely Gaussian, Otsu and Black Hat transformation and is represented in Figure 6.

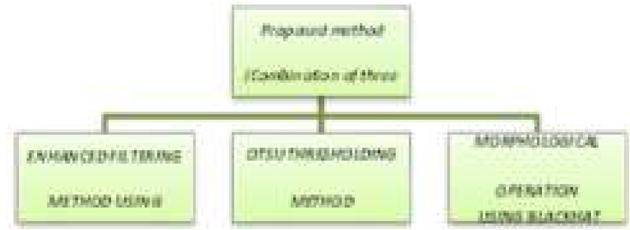


Figure 6: Proposed Hybrid method

An Enhanced filtering method using Gaussian

The preservation of edge is better in Gaussian than other filters like mean and median. But the process of detecting the discontinuities using Matlab functions is not efficient for real time applications. Hence, to overcome this problem, the enhanced standard deviation filter is used. The enhanced filtering uses Gaussian filtering for removing the noise and Anisotropic gauss filter is used for smoothing. The word anisotropy is defined as a variation of magnitude along with the direction. It not only removes the noise, but also preserves the edge information. The normal gaussian function G(x) is given by

$$G(X) = \frac{1}{2\pi\sigma^2}\, e^{-(\frac{x^2+y^2}{2\sigma^2})} \qquad (1)$$

Figure 7 shows the output of real time car image with variable sigma using Gauss function. From Figure 7, it is clear that the output image with **σ=** 0.1 is better than the image with **σ=** 0.5 and **σ=** 4.

The analytical expression of Anisotropic is given as,

$$A(X) = \frac{1}{2\pi\sigma x\sigma y}\, e^{-(\frac{x^2}{2\sigma^2 x} + \frac{y^2}{2\sigma^2 y})} \qquad (2)$$

where σ_x and σ_y are the standard deviation with dimension x and y respectively, and A(x) is denoted as Anisotropic. Table 1 shows the various output values of Gaussian G(x) with variable sigma. The structural properties of Gaussian are given in Table 2.

(a) Smoothed image σ = 0.1

(b) Smoothed image σ = 0.5

(c) Smoothed image σ = 4

Figure 7: Smoothed image with sigma (a) 0.1 (b) 0.5 and (c) 4

Table 1: G(x) with Variable SIGMA

S.no	SIGMA (σ)	Resulted Output
1	0.1	Clear and visible
2	0.5	Clarity and visibility is poorer than 0.1
3	4	Difficult to visualize due to Blur

Smoothed image $\sigma_x = 1$, $\sigma_y = 0.5$

Figure 8: Smoothed image

Table 2: Rationale of Gaussian Properties

S.no	Properties	Rationale
1	Cascade	Self-similar function
2	Anisotropic	Standard deviations are not same for a different direction
3	Rotational symmetry	Smoothing is same in all directions
4	Fourier transform	Used when the images are corrupted by the high frequency component.
5	Separability	Separation of the standard deviation
6	Normalization	Integral is unity

Among the various properties listed in Table 2, The propsed method uses the anisotropic property for different dimension.

Figure 9 shows the output of edge detection for the collected real time source image. It is difficult to detect the exact car boundary due to noise distribution caused by tree shadow. Hence it results in failure of locating the required plate candidate. So to overcome this problem, the proposed method replaces Gaussian with anisotropic, hysteresis with Otsu for thresholding image. It avoids the manual reset of thresholding for image segmentation.

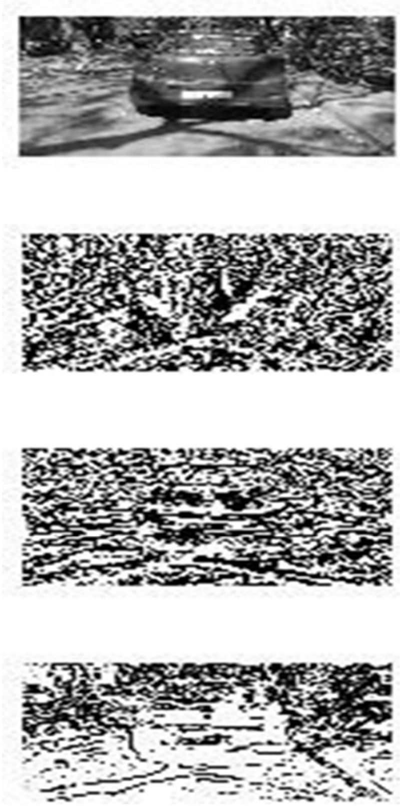


Figure 9: Failure of detecting LP without filter due to environmental noise

OTSU Thresholding

It is a region based thresholding method which is used to detect the ROI. It is very effective in separating the required candidate region. It minimizes the within class variance. It determines and divides, whether the pixel falls into the foreground or background by computing the histogram as shown in Figure 10.

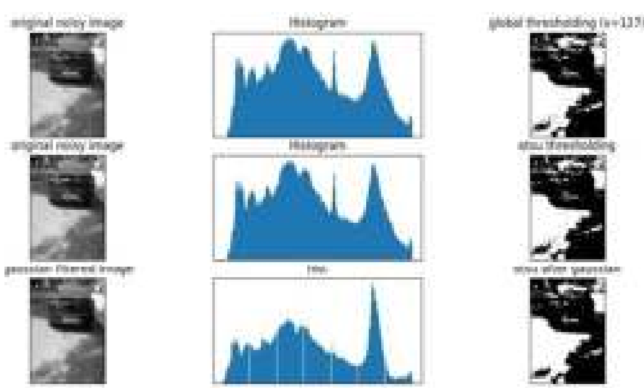


Figure 10: Original noisy image with and without Otsu along the Gaussian

The weighted within class is expressed as follows:

$$\sigma^2_w = w_b\sigma^2_b + w_f\sigma^2_f \qquad (3)$$

Where,

$\sigma^2_w \longrightarrow$ Within class variance

$W_b \longrightarrow$ Weight of Background

$\sigma^2 \longrightarrow$ Background variance

$W_f \longrightarrow$ Weight Boreground

$\sigma^2 \longrightarrow$ Foreground variance

Between class variance is expressed as,

$$\sigma^2_b = \mu - \sigma^2_w \qquad (4)$$

where,

$\sigma^2 \longrightarrow$ Background Variance

$\mu \longrightarrow$ Mean ($\mu = W_b\mu_b + W_f\mu_f$)

$\sigma^2 \longrightarrow$ Within class Variance

The Otsu thresholding is computationally intensive. It sets the threshold value dynamically based on peak value of histogram as shown in Figure 9.

Algorithm for Otsu thresholding
step1: Compute the histogram of each intensity value
step2: Set up the initial value of weight W and Mean μ
step3: Set the random initial threshold value a: update W and μ b: Compute the variance
step4: Get the corresponding maximum threshold value

Mathematical Morphological Transformation

The mathematical morphology is primarily a transformation process. It is defined on the binary images of 0s and 1s which corresponds to foreground and background. It is carried out by probing the structuring element over the binary image using a set theory union, intersection, complement, etc. Here, the operation blackhat is used for scissoring the license plate. It is the difference between closing and its source image and it is expressed as,

BH = Close(SI,element)-SI image (5)

Where,

BH - BlackHat

Close - Dilation followed by Erosion

SI - Source Image

Generally Erosion erodes away or removes the pixel value of the Foreground boundary objects and Dilation is opposite of Erosion which adds pixels to the boundary of the object.

After locating the license plate, the major step to be carried out is the perspective transformation for extracting the plate candidate [Ramalingan S., 2012]. Figure 11 shows the Overall Architecture of AGOB method. The overall Pseudo code is given below:

Overall Pseudo code for Plate Extraction

```
Step1: Load the Src
        image Src—
        source image
Step2: Resize the given source image
Step3: Apply black hat transformation by taking the
       difference between source image and opening
Step4: Detect the License Plate using Aspect ratio
Step5:Draw the bounding box over selected candidate
       License Plate
Step6: Create SE to perform morphological
        operation SE—Structuring element for
        extracting LP
Step7:Apply Gaussian for smoothing and Otsu
       Thresholding for extracting Required Region of
       Interest (RROI)
Step8: Get the Perspective transformation of LP

Step9: End
```

RESULT AND ANALYSIS

Table 3 shows the implementation results, analysis with perspective transformation and threshold using python and Open CV. License Plate Detection Rate (LDR) is formulated as follows:

$$LDR = \frac{\text{Number of correctly Detected LPs}}{\text{Number of all ground truth LPs}}$$

Table 4 shows the success ratio of correctly detected License plate for benchmark dataset and real time Indian dataset. Table 5 shows the comparative analysis of various existing methods with the proposed method.

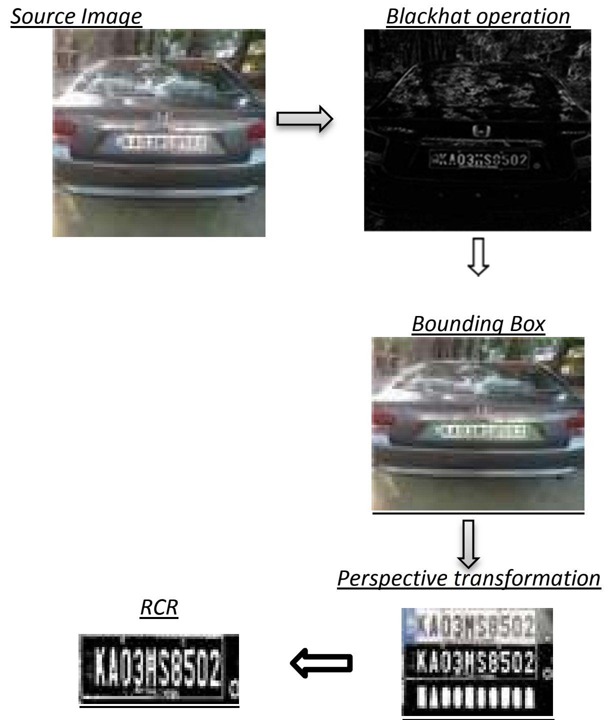
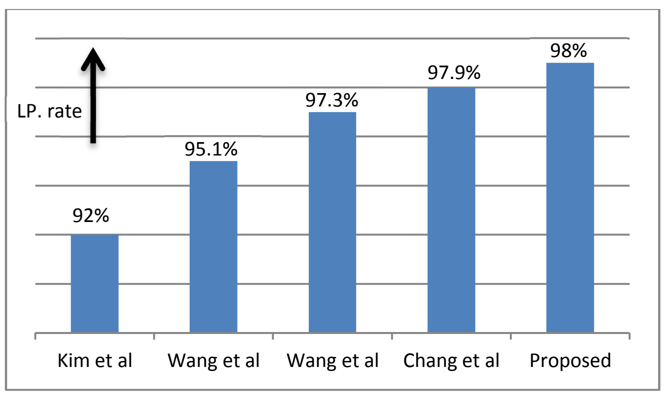


Figure 11: Proposed architecture diagram



Acronym
1.ICLPR - Indian Car License PLate Recognition System
2.RCR - Required Candidate Region
3.AGOB - Anisotropic Gaussian with Otsu and BlackHat
4. SI - Source Image
5.RROI - Required Region Of Interest
6.LDR -License plate Detection Rate
7.LPL - License Plate Localization

Table 3: Bounding Box and Cropped Region

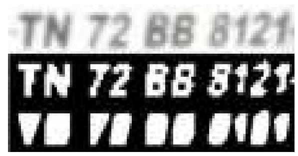
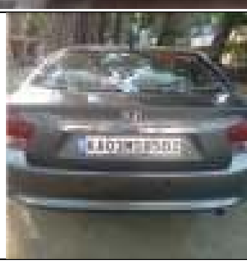
Sl. No.	Image	Bounding Box	Plate candidate with perspective transform	Region of Interest
1				
2				
3				
4				
5				

Table 4: Efficiency of Plate Candidate

S. No.	Techniques	Sample dataset	Total no of images	Correctly detected	Undetected	LDR (License Plate Detection Rate)
1	Bounding box	Benchmark	95	95	NIL	100%
2	Plate candidate	Benchmark	95	95	NIL	100%
3	Bounding box	Real time	95	91	4	96%
4	Cropped ROI	Real time	95	92	3	97%

Table 5: Comparison with Existing method

S. No.	Existing Method	Data Set	Type Of The Image	LPL Rate
1	Proposed	Indian	Real time noisy color image	98%
2	Chang et al. [12]	Taiwan	Colour	97.9%
3	Wang et al. [13]	China	Colour	95.1%
4	Kim et al. [14]	Korea	Colour	92.7%
5	Wang et al. [15]	Taiwan	Greyscale	97.3%

CONCLUSION

This paper presented a novel efficient LP hybrid scheme that uses Anisotropic Gaussian Blackhat algorithm. The proposed scheme is implemented in python using Open CV and Validated using standard dataset and real time dataset. It is found that the proposed AGOB has better LPD and LPL rate. The extracted license plate is further used for the process of recognizing the character by training the whole candidate region using Deep learning Convolution Neural Network (CNN).

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