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Comparison of Vehicle License Plate Detection Algorithms and LP Character Segmentation and Recognition using Image Processing

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***Abstract**: In the last couple of decades, the number of vehicles has increased drastically, consequently, it is becoming difficult to keep track of each vehicle for purpose of law enforcement and traffic management. License Plate Detection is used increasingly nowadays for the same. The system performing the task of License Plate detection is known as the LPR system which generally consists of three steps: Detection of the License plate, Segmentation of License plate characters, and Recognition of the characters of the License Plate (LP). But in real-world scenarios, the various lighting conditions, camera angle, and rotation degrades the accuracy of License Plate region detection, which in turn causes inaccurate segmentation and recognition of the license plate characters hence leading to low accuracy of the LPR systems. Therefore, it is vital to consider the most promising algorithm or technique for LP detection. In this paper, we will be analyzing and comparing five different methods for license plate detection: Morphological reconstruction, Sobel Operator, Top Hat Transform, Histogram processing, and Canny Edge detection. We will be experimentally applying these techniques on real-time captured vehicle images, using the Bounding Box algorithm for character segmentation, performing license plate character recognition using Template matching, and subsequentially evaluating and demonstrating the LPR system that promises the most accurate and efficient results.*

***Keywords**: License Plate Detection, Image Processing, Bounding Box, Morphological Reconstruction, Top Hat Transform, Histogram*

I. INTRODUCTION

License plate recognition (LPR) is a system to identify a vehicle by recognizing the captured license plate image. It has been applied in numerous applications such as automatically identifying vehicles in a car park, curbing traffic, and road safety violations, and detecting and verifying stolen vehicles. In today's world, there is a vast number of commercial LPRs. These existing systems can broadly be classified into two types. In the first method, commercial Optical Character Recognition (OCR) software is used to recognize the characters of a license plate. The second method comprises of a learning-based approach towards character identification.

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Both of these models claim high accuracy when used under controlled conditions and the cameras are mounted in fixed locations without mobility. However, with poor illumination conditions and continuous movement of vehicles, the accuracy gets impaired. When using an OCR for character recognition, it is crucial to correctly remove the license plate boundaries after the license plate is detected. No matter which OCR is used, the Character Segmentation and recognition accuracy will be significantly reduced if the license plate region is not detected precisely. Therefore, license plate detection plays a critical role in the LPR system. For this purpose, we will be analyzing some of the most extensively used state-of-the-art LP detection techniques and experimentally demonstrating which technique shows the most promising accuracy and precision in the detection of the LP region. Furthermore, since the characters on a license plate need to be highlighted and separated from the background area to improve recognition accuracy, image segmentation is one of the key processes in the system. It partitions the image into some constituted parts so that each constituted part contains one character that can be extracted for further processing. There are two unique approaches to Image segmentation: contour-based and region-based techniques [1]. Contour based method is a gradient-based segmentation method. It is based on the objective of detecting edges in an image directly from their high gradient scales. Edge or boundary-based approaches [2][3], and active contour-based methods [4][5], are some good examples of the technique. On the other hand, in region-based methods, the segmentation is usually based on discontinuity and similarity of the gray level of the image or other features, such as color, texture, shape, etc. [6]. However, most of these methods don't work well in scenarios where the characters are connected to each other or with the boundary in the captured video data. Moreover, boundaries are often shown in a similar pattern to the characters, and sometimes boundaries are broken [7]. Therefore, the recognition rate is very low due to the poor segmentation of characters. In this paper, we first present an overview of the different approaches to license plate detection and then apply the Bounding Box algorithm for character segmentation [8]. All these techniques are applied to real-time vehicle images to demonstrate the capability of these algorithms in a real-world LPR system. The proposed model can successfully differentiate the character regions of the license plate from the non-character regions accurately and efficiently.

The remaining section of the paper is organized as follows:

Section 2 throws light on the existing methodologies and related literature work around the LPR systems.

Section 3 comprises the methodology proposed in this paper with subsections for image pre-processing, license plate detection techniques, their implementation as well as character segmentation and recognition algorithms. Section 4 shows the experimental comparison results obtained in terms of their accuracy and finally, Section 5 concludes this paper.

II. RELATED WORK

Vehicle license plate detection, character segmentation, and recognition are very important in secured transport systems for high-speed applications. Various models and algorithms have been devised to improve the existing LPR systems. Christos-Nikolaos, Ioanni, Ioannis, Vassili and Eleftherios [9] used morphological reconstruction, Sobel edge detection, and histogram processing techniques for license plate detection forming a layered model for LP detection.

Feng Yang and Fang Yang [10] presented a method using Top Hat transform to detect the license plate. They described the smart vehicle screening system, which can be installed into a tollbooth for automated recognition of vehicle license plate information using a photograph of a vehicle. Then, a computerized system could be used to manage the payment of fees for parking spaces, motorways, bridges, or tunnels, among other things. Koval and Turchenko considered an approach to identify vehicles by recognizing their license plates using image fusion, neural networks, and threshold techniques as well as demonstrated realistic experimental results [11].

License plate detection, character segmentation, and recognition are the three phases that typically makeup vehicle license plate recognition systems. When reading characters on a license plate one by one after the license plate has been detected, it is crucial to accurately segment the characters [12][13]. Numerous elements, such as the edges and frames of license plates, may have an impact on the segmentation process. If the characters are not properly segregated, the recognition accuracy will be significantly lowered. Xiangjian & Zheng presented an efficient algorithm for character segmentation on a license plate. They have used the AdaBoost algorithm for license plate detection. It is based on precise and reliable license plate skew and slant correction that merges with boundary edge removal. The algorithm is reliable and can be applied to real-time applications [14].

Automatic Number Plate Recognition (ANPR) is a real-time embedded system that identifies the characters directly from the image of the license plate. It is an active area of research. Vehicle number plate recognition (VNPR) has been the subject of extensive research in recent times. The specifications for an automatic number plate recognition system differ for each nation due to the various types of number plates that are employed. Bajaj, Varun & Patwari proposed a number plate localization and recognition system for vehicles in India [15]. This technique, which was created using digital image processing, may simply be integrated into commercial car park systems for use in tracking customer access to parking facilities, securing the use of car spaces, and preventing automobile theft. The suggested model for number plate localization combines morphological operation with area criteria assessments. Bhatt and Mehandia achieved segmentation of the plate characters by the application of region props function in MatLab, labeling, and fill hole approach. The character recognition was accomplished with the aid of optical characters through the process of Template matching. [16]. Ganapathy and Lui proposed license plate localization algorithm is based on a combination of morphological processes with a modified Hough Transform approach and the recognition of the license plates is achieved by the implementation of the feed-forward backpropagation artificial neural network [17].

Automatic number plate recognition is a well-known proposal in today's world due to the rapid growth of cars, bikes, and other vehicles. Image processing is extensively used for license plate detection in automatic number plate recognition systems. This system can be used in highly populated areas as well as highly restricted areas to easily identify traffic rule-violated vehicles along with the owners' names, addresses and other information [18]. This can also be used in the case of car usage in terrorist activities, smuggling, invalid number plates, stolen cars, and other illegal activities. Another purpose where it can be used is in highway electronic toll collection. An image of the car number plate is captured, and detection is using image processing algorithms. Character segmentation which locate the alphanumeric characters on a number plate. Then the segmented characters are translated into text entries using optical character recognition(OCR) [19]. The existing ANPR systems even though fully operational, do not promise high efficiency and accuracy. These systems are developed using different methodologies but some factors like vehicle speed, different font styles, font sizes, the language of the vehicle number, and light conditions are required to be explored. These dynamic parameters can significantly reduce the system's overall recognition rate. ANPR systems scan the vehicle license plates using optical character recognition, and most importantly they can recover them on a constant need basis [20][21]. Figen and Fikriye localized the plate using Otsu's thresholding method and the plate features [22]. They used vertical and horizontal histograms for character segmentation and an algorithm based on Probabilistic Neural Networks for character recognition. Every model has its own set of pros and cons with a common aim to optimize the precision of LPR systems.

III. METHODOLOGY

The proposed model architecture starts with process of image acquisition where the image is captured using a high-quality pixel camera. Before moving on to the actual License plate detection, the acquired image is first pre-processed and made fit for further application of algorithms. After this, once the license plate is successfully detected, we move on to the next stage of character segmentation of the license plate. To summarize, the proposed model will sequentially:

- Apply a perspective transform to extract the license plate region from the car, obtaining a top-down view more suitable for character segmentation.
- Perform a connected component analysis on the license plate region to find character-like the image.
- Utilize contour properties that aid in segmenting the foreground license plate characters from the background of the license plate and recognizing characters.

The methodology section is subdivided discussing each one of the above-mentioned stages in detail. Figure 1 below shows the LPR system's process flow.

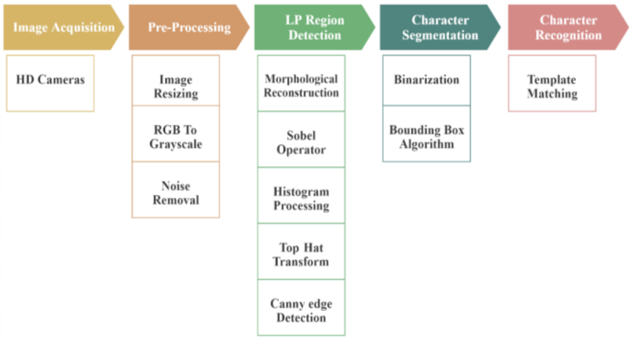

Fig. 1. LPR System Process Flow

A. Pre-processing

The images acquired from the various HD cameras are by default all RGB-colored images. As part of pre-processing, the images are first uniformly resized to 480x620. Next, after the resizing, the RGB images are then converted to grayscale images in order to remove color redundancy and obtain a compact and optimal image representation which can be further used for processing [23].

The Luminosity algorithm was used for the RGB to grayscale conversion [24]. Following steps were used to pre-process the images for the implementation of the proposed model:

- The original RGB vehicle image was read as input.
- All three color components: Red, blue and green were extracted from the RGB image and formulated into 3 different 2-D matrices consisting of i rows and j columns.
- Another matrix consisting of the equivalent number of rows and columns as the RGB image was created.
- A weighted sum of the red, green, and blue color components of the RGB pixel value at location (i, j) was computed using the equation (1). This weighted sum was populated as the pixel value at the same location (i, j) in the new matrix.

Grayscale Value at (i, j) = 0.2989 * R(i, j) + 0.5870 * G(i, j) + 0.1140 * B(i, j) (1)

Using this algorithm, we converted all the RGB input images to grayscale. Next, we remove the extraneous noise captured in the images before processing it further. For this, we will be using the Bilateral filter, which is a non-linear, noise removal filter that preserves the edges in the image, which is vital for achieving our objective of license plate detection.

The bilateral filter replaces the intensity of each pixel with a weighted average of its neighboring pixel intensities [25]. The weight was calculated based on the Gaussian distribution given by the below equation (2)

$$BF(p) = \frac{1}{W}\sum_q G_{\sigma_s}(\|p-q\|)G_{\sigma_r}(|I_p - I_q|)\, I_q \qquad (2)$$

Where w → normalization factor

p → pixel value to be filtered

σ_s → special extent of the kernel used for smoothing

σ_r → range kernel that gives the minimum amplitude of an edge

G → Gaussian distribution

Figures 2 and 3 below show the original RBG image acquired and the converted filtered grayscale image respectively.

Fig. 2. Original RGB Input Image

Fig. 3. Filtered Grayscale Image

IV. VEHICLE LICENSE PLATE DETECTION

In this paper, we will be comparing the 5 most extensively used image processing techniques for Vehicle License Plate detection. Later in the proceeding section, the subsequent character segmentation using the Bounding Box algorithm will be discussed.

A. Using the Mathematical Morphology

Morphological image processing is a sequential procedure of nonlinear operations based on the shape or morphology of features in an image. The operation is based on the relative ordering of the pixels and not on their values [26]. The morphology is performed using a structuring element which is also a binary image. Basic operations for the image morphology is erosion and dilation.

• Erosion

The erosion of a binary image f with structuring element s produces an image g with ones in all locations (x,y) of a structuring element's origin at which that structuring element s fits the input image.

For instance, Figure 4 is eroded with a structuring element of size 3x3 (Figure 5) to produce Figure 6.

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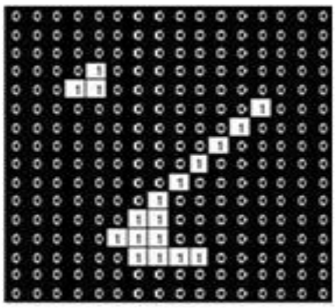

Fig. 4. Input Image

1	1	1
1	1	1
1	1	1

Fig. 5. Structuring element

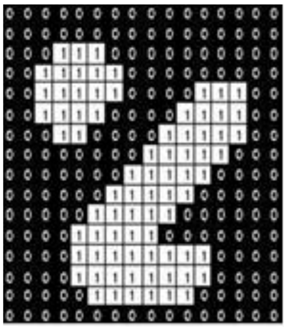

Fig. 6. Eroded Image

• Dilation

The dilation of a binary image f with structuring element s produces an image g with ones in all locations (x,y) of a structuring element's origin at which that structuring element s hits the input image. For instance, Figure 4 is dilated with a structuring element in Figure 3.

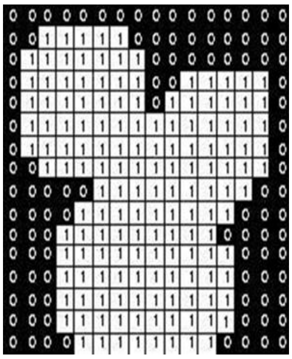

Fig. 7. Dilated Image with a Structuring element

Morphological image processing is a sequential procedure The basic morphological operations (erosion and dilation) are used to find the region of interest. The image is dilated and eroded with a specific structuring element and a morphological gradient is used in order to detect the edges in the image. Following are the steps performed as part of the proposed model:

1. The Image grayscale input image is dilated and eroded with the 'disk' structuring element of radius 1 given in Figure 5. Figures 8 and 9 show the eroded and dilated images respectively.

Fig. 8. Eroded Image

Fig. 9. Dilated Image

2. Next, we use a binary matrix $\oplus$ to enhance the edges. Equation 3 was used for calculating the Morphological Gradient.

$$G(f) = f \oplus b - f \ominus b \quad (3)$$

Where $\oplus \rightarrow$ Dilation operator
$\ominus \rightarrow$ Erosion operator
f $\rightarrow$ Input image
b $\rightarrow$ Structuring element

Fig. 10. Image with enhanced edges

3. Image is converted to a binary image and all the holes are filled. After filling the holes, the connected components having an area of less than 100 pixels are removed and the final detected license plate image is shown in Figure 11 below.

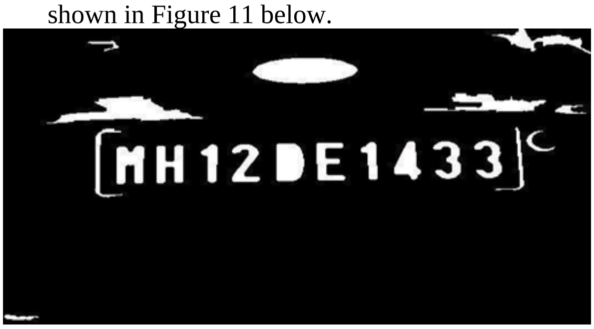

Fig. 11. Final LP Detected Image

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B. Using the Sobel operator

The Sobel operator is a derivative mask that can be used to detect vertical and horizontal edges. After detecting the edges, all the non-candidate edges are removed to find the License Plate Region [27].

-1	0	1	-1	-2	-1
-2	0	2	0	0	0
-1	0	1	-1	-2	-1

Horizontal Vertical

Fig. 12. Sobel Kernels

The following are the steps involved:

1. Sobel edge operator is applied to the filtered grayscale image to detect the edges. Figure 12 shows the image obtained after applying the vertical and horizontal Sobel kernels (Figure 13) to the input image.

Fig. 13. Image after applying the Sobel operator

2. The horizontal and vertical edges are removed by first dilating the image with the horizontal line and then dilating with the vertical image.
3. Holes in the image are filled and borders along the edges are removed.
4. The resulting image is eroded two times with a disk structuring element of radius 1 given in Figure 5. The holes are filled again to obtain the detected LP region as shown in Figure 14 below.

Fig. 14. Detected LP Region

5. The above image is multiplied with the grayscale image to find the actual LP detected as depicted in Figure 15.

Fig. 15. Final LP Detected

C. Using Histogram Processing

A graphical presentation of an image's pixel density as a function of intensity is called an image histogram. Histograms comprises of groups or bins where each individual bin denotes a specific magnitude of intensity [28] [29]. The below steps were used to detect the license plate using histogram processing. The license plate image's pixel intensity distribution is represented graphically by the histograms given below. The pixel intensity is plotted on the X-axis, while the frequency is plotted on the Y-axis.

1. To find a horizontal histogram, the algorithm traverses through each column of the filtered grayscale image. The algorithm begins processing the second pixel of each column from the top. The difference between the second and first pixels is calculated. The difference will be added to the total sum of differences only if it passes a certain threshold. Then, the algorithm will move downwards to calculate the difference between the third and second pixels. The histogram obtained from the horizontal edge processing of the image is shown in Figure 17.
2. The Horizontal histogram is smoothed using the low pass filter.

Fig. 16: Dilated Grayscale Input Image

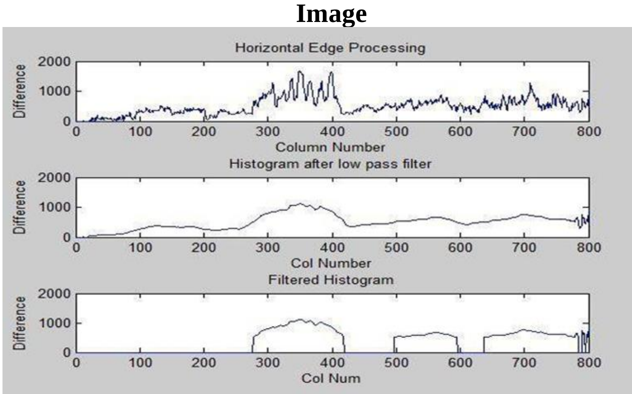

Fig. 17: Histogram obtained from horizontal edge processing

3. So on, it moves until the end of a column and calculates the total sum of differences between neighboring pixels. In the end, we create a column-wise sum in the form of an array. The vertical histogram is constructed using the same technique. In this case, rows are processed instead of columns, and the histogram obtained after vertical edge processing is shown in Figure 18.

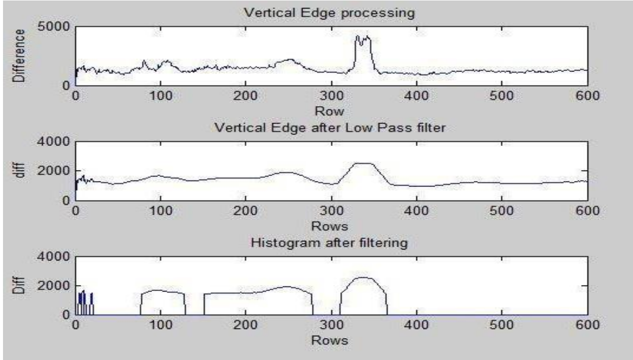

Fig. 18: Histogram obtained from vertical image processing

4. The histogram values change drastically between consecutive columns and rows. Therefore, to prevent the loss of important information in upcoming steps, it is advisable to smooth out such drastic changes in the values of the histogram. To achieve this, we pass the histogram through a low-pass filter. While performing this step, each histogram value is averaged out considering the values on its right-hand side and left-hand side. This filter is applied on both vertical as well as the horizontal histogram.
5. Then the unwanted regions with low histogram values are removed and the regions having high histogram values become the eligible candidates for LP regions as they have a higher probability of containing the LP. The candidates obtained are shown in Figure 19 below.

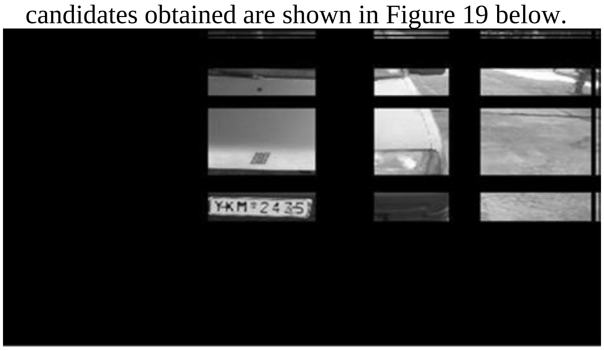

Fig. 19: LP region candidates

6. Out of all the found candidate regions, the one with the highest histogram values is considered the final License plate as shown in Figure 20.

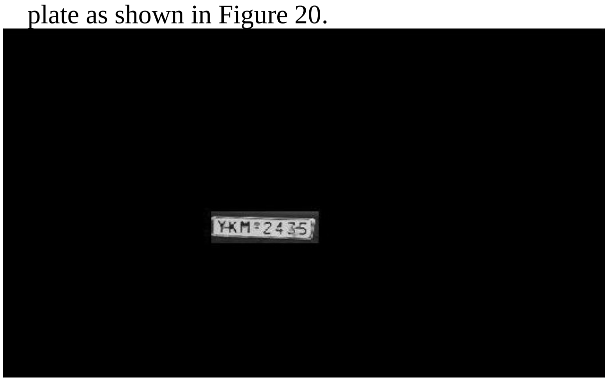

Fig. 20: LP Detected

D. Using the Top Hat transform Algorithm

The Top-hat transformation is one of the Mathematical morphologic transformations. It is highly effective in searching for contrast intensities in an image, differentiating black pixels in white background and white pixels in black background. The equation for Top Hat transform is given by equation (4)

$$HAT(f) = f - (f \circ g) \qquad (4)$$

Where f → Input image

g → Structuring element. In this paper, we used a 3x3 structuring element for implementation purposes.

$$f \circ g = (f \ominus g) \oplus g \qquad (5)$$
$$f \bullet g = (A \oplus g) \ominus g \qquad (6)$$

Structure g erodes vehicle license plate image f using Equation (5) and structure g dilates license plate image f using Equation (6). Open arithmetic or erosion can remove small unnecessary objects, segment objects at smooth places, and smooth the edges of large objects [10]. Close arithmetic or dilation can fill in small irregular holes of objects, join similar neighborhood objects, and smooth the edges of objects. Below are the steps that were performed for the detection of LP using the Top Hat algorithm.

1. Vertical gradient of the filtered grayscale input image is calculated using equation (7) given below. Here f is the input image with pixel value at location (i,j) and Figure 21 shows the image after the application of the vertical gradient.

$$g_v(i,j) = | f(i,j+1) - f(i,j) | \qquad (7)$$

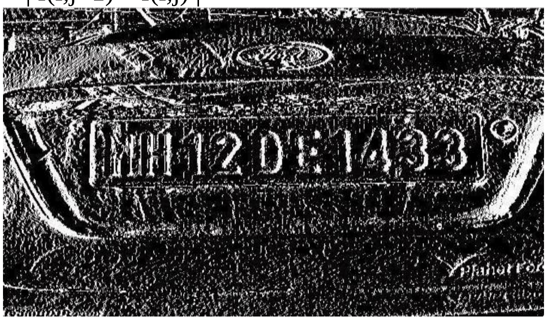

Fig. 21. Application of Vertical Gradient

2. Horizontal candidates are calculated by the horizontal histogram processing function given by equation (8) here.

$$T_H(i) = \sum_{j=1}^{n} g_V(i,j) \qquad (8)$$

3. Horizontal projection of the input image as obtained in the previous step, is corrupted with a lot of burrs. Hence to solve this issue, we introduce the Gauss filter for the removal of these burrs. The horizontal candidates are filtered using equation (9) below.

$$T_H(i) = \frac{1}{k}\left\{T_H(i) + \sum_{j=1}^{w}\begin{bmatrix}T_H(i-j)h(j,\sigma) + \\ T_H(i+j)h(j,\sigma)\end{bmatrix}\right\} \qquad (9)$$

Where $T_H(i)$ → original projection value,

$T'_H(i)$ → filtered projection value,

$1<i<m$

w →width of the smoothness region,

h(j,σ) → Gauss filter

σ →parameter of Gauss filter

k → threshold value set to 4 for simulation

Figure 22 below shows the horizontal candidates obtained after applying the Gaussian filter.

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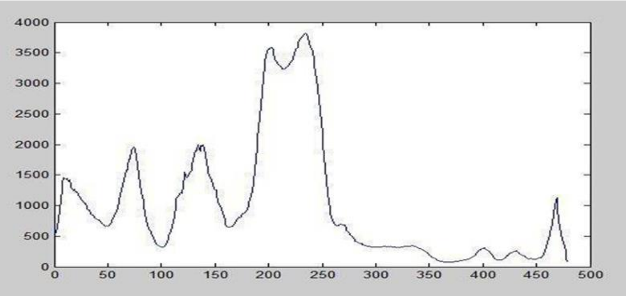

Fig. 22. Smoothed Horizontal Candidates

4. Next, a threshold T was calculated using equation (10) given below.

$$T = t * a \quad (10)$$

Here, a → Average of the filtered projection value $T_H(i)$

t → Weight parameter which was set to 7 in our implementation based on experimental results.

5. Only those candidate regions whose values were above the threshold calculated in the previous step were filtered as shown in Figure 23, and the remaining of the smoothed horizontal histogram candidates were discarded.

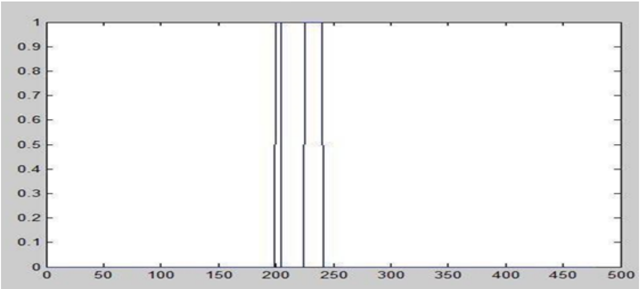

Fig. 23: Candidate Rows

6. Now, we need to amalgamate the original image based on the candidate rows calculated in the above step to find the License Plate region as shown in Figure 24.

Fig. 24. Detected License Plate

E. Using the Canny Edge Detection Method

The Canny Edge detection algorithm is mainly used for detecting edges in images that are corrupted by noise [30]. The process of canny edge detection was applied on the input image using the below steps:

A Gaussian filter was applied using the below equation (11) to smooth the grayscale image in order to remove the noise.

$$f'(i,j) = GF(i,j) * f(i,j) \quad (11)$$

where f' → Filtered image

GF → Gaussian filter given by (12)

$$GF(i,j) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left|-\frac{i^2+j^2}{2\sigma^2}\right|} \quad (12)$$

f → Original grayscale image with i,j representing pixel values at a given point.

1. Next, we computed the intensity gradients of the image using equation (13) below

$$IG(i,j) = \sqrt{g_x^2(i,j) + g_y^2(i,j)} \quad (13)$$

2. Pixels that did not belong to any of the edges detected, were removed using non-maximum suppression.
3. Potential candidates for edges were estimated using thresholding. For the proposed model, a threshold value of 4 was used. Pixels with a value above 4 were considered, and the pixel below that was discarded.
4. Based on the previous step, Finalize the detection of the edges by suppressing all the other edges.

Next, we move on to the next stage of the LPR model i.e., character segmentation and recognition of the vehicle license plate.

V. SEGMENTATION AND RECOGNITION OF LICENSE PLATE CHARACTERS

After the detection of the edges, the license plate region image is converted to a binary image and the characters are segmented. The bounding Box algorithm is applied to segment the characters from the image. Along with the segmented characters, some noise is also segmented which can be removed after the processing [31]. The following steps were performed as part of Bounding extraction:

1. Detected license plate image is converted into binary using thresholding as shown in Figure 25. For this, we removed all the objects in the image containing fewer than 30 pixels. Hence, all grayscale values less than 30 were marked as 0, and the remaining equivalent or above the threshold value is marked as 1.
2. The 1s denote white color or the foreground and the 0s denote black color or the background [32].

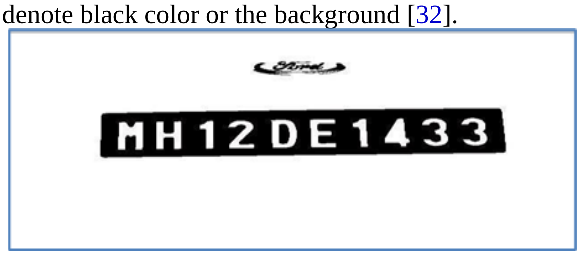

Fig. 25. Binary Image

3. Once the image is converted to binary, we apply the 4-Connectivity rule to label the components.
4. Pixels that are 4 adjacent to each other are marked as 4 connected and hence labels are formed based on the grouping of these interconnected components.
5. Properties of these connected image regions are measured and then cropped separately into different boxes and finally, the Bounding Boxed objects are extracted as shown in Figure 26.

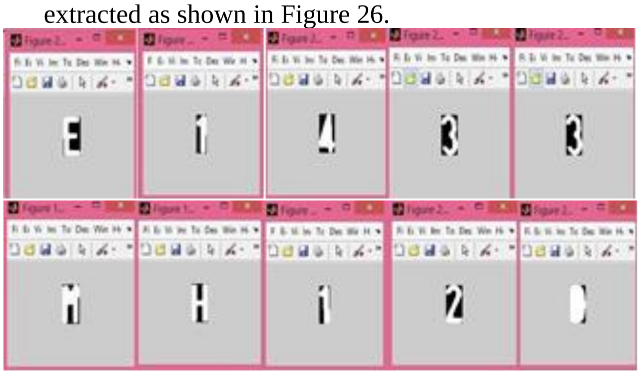

Fig. 26. LP Segmented characters

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6. The separate characters segmented from the previous step are then recognized using the Template matching method in which the segmented character is correlated with template data containing A-Z and 9-0 data parameters.
7. The highest correlation matches are then transferred as output to a .txt file giving the final license plate recognized number as shown in Figure 27 below.

Fig. 27. Recognized License Plate Number

VI. RESULT

After implementing all the five different License plate detection techniques discussed above on a certain set of real-time vehicle images, it was observed that the Sobel Edge Detection algorithm gave the highest accuracy of 92% while maintaining the least amount of error percentage. Following the Sobel operator was the histogram processing LP region detection technique with 89% precision as shown in Table I below.

Table I: Accuracy Comparison for LP Detection Algorithms

Method Name	No. of Input Image	No. of Images with Detected LP	Accuracy (Percentage)	Error (Percentage)
Mathematical Morphology	500	390	78%	22%
Sobel Edge Detector	500	460	92%	8%
Histogram Processing	500	445	89%	11%
Canny Edge Detection Method	500	335	67%	33%
Top Hat Transform	500	360	72%	28%

VII. CONCLUSION

With continuously improving transport infrastructure and ever-growing number of vehicles, systems like LPR License Plate Recognition play a vital role in establishing traffic law and order and ensuring smooth and organized vehicle management. Due to various angles, illumination constraints and accelerated mobility while capturing real-time dynamic images of the vehicles, the detection of license plate poses a great challenge. In this paper, we experimentally analyzed the most extensively used state-of-the-art techniques for LP detection and further applied the Bounding box algorithm for character segmentation and template matching for character recognition of the license plate. Before doing so, certain pre-processing was done on the originally captured images. Images were resized for uniform analysis. RGB color space was converted to grayscale images for smoother and faster processing and lastly, any extraneous noise captured in the image was removed using median filtering. Finally, it was observed that the Sobel operation technique produced the best results. The other methods especially the Histogram processing technique is close to the Sobel edge detector method to detect the License plate region precisely and more efficiently.

REFERENCES

1. Abubakar, Fari. (2012). A Study of Region-Based and Contourbased Image Segmentation. Signal & Image Processing : An International Journal. 3. 15-22. 10.5121/sipij.2012.3602. [CrossRef]
2. Hsiao, Ying-Tung & Chuang, Cheng-Long & Jiang, Joe-Air & Chien, Cheng-Chih. (2005). A Contour based Image Segmentation Algorithm using Morphological Edge Detection. Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics. 3. 2962 - 2967 Vol. 3. 10.1109/ICSMC.2005.1571600.
3. Hemalatha, R.J. & Thamizhvani, T.R. & Dhivya, A. & Joseph, Josline & Babu, Bincy & Chandrasekaran, R.. (2018). Active Contour Based Segmentation Techniques for Medical Image Analysis. 10.5772/intechopen.74576. [CrossRef]
4. Jiaqing Miao, Ting-Zhu Huang, Xiaobing Zhou, Yugang Wang, Jun Liu, Image segmentation based on an active contour model of partial image restoration with local cosine fitting energy, Information Sciences, Volume 447, 2018, Pages 52-71, ISSN 0020-0255, https://doi.org/10.1016/j.ins.2018.02.007. [CrossRef]
5. Malik, J., & Maire, M. (2009). Contour detection and image segmentation.
6. S.Karthick , Dr.K.Sathiyasekar , A.Puraneeswari, Article:A Survey Based on Region Based Segmentation, International Journal of Engineering Trends and Technology(IJETT), 7(3),143-147, published by seventh sense research group [CrossRef]
7. Yu, H., Sun, P., He, F., & Hu, Z. (2021). A weighted region-based level set method for image segmentation with intensity inhomogeneity. PloS one, 16(8), e0255948. https://doi.org/10.1371/journal.pone.0255948 [CrossRef]
8. K. M. Babu and M. V. Raghunadh, "Vehicle number plate detection and recognition using bounding box method," 2016 International Conference on Advanced Communication Control and Computing Technologies (ICACCCT), 2016, pp. 106-110, doi: 10.1109/ICACCCT.2016.7831610. [CrossRef]
9. Anagnostopoulos, Christos-Nikolaos & Anagnostopoulos, Ioannis & Psoroulas, I.D. & Loumos, Vassili & Kayafas, Eleftherios. (2008). License Plate Recognition From Still Images and Video Sequences: A Survey. Intelligent Transportation Systems, IEEE Transactions on. 9. 377 - 391. 10.1109/TITS.2008.922938. [CrossRef]
10. Feng Yang and Fan Yang, "Detecting license plate based on top-hat transform and wavelet transform," 2008 International Conference on Audio, Language and Image Processing, 2008, pp. 998-1003, doi: 10.1109/ICALIP.2008.4590154. [CrossRef]
11. V. Koval, V. Turchenko, V. Kochan, A. Sachenko and G. Markowsky, "Smart license plate recognition system based on image processing using neural network," Second IEEE International Workshop on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, 2003. Proceedings, 2003, pp. 123-127, doi: 10.1109/IDAACS.2003.1249531. [CrossRef]
12. K. V. Murygin, “Normalizing the image of a vehicle license plate and segmentation of characters for subsequent recognition,” Iskusstvennyi Intellekt, No. 3, 364–369 (2010)
13. He, Xiangjian & Zheng, Lihong & Wu, Qiang & Jia, Wenjing & Samali, B. & Palaniswami, Marimuthu. (2008). Segmentation of characters on car license plates. 399-402. 10.1109/MMSP.2008.4665111 [CrossRef]
14. Image Recognition for Automatic Number Plate Surveillance P.Meghana, S. SagarImambi, P. Sivateja, K. Sairam International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8 Issue-4, February 2019
15. Bajaj, Varun & Patwari, Madhurima & Mitra, Gaurav. (2017). AUTOMATIC LICENSE PLATE RECOGNITION.
16. Bhat, R., & Mehandia, B. (2014). RECOGNITION OF VEHICLE NUMBER PLATE USING MATLAB.

17. Ganapathy, V. & Lui, Dennis. (2008). A Malaysian Vehicle License Plate Localization and Recognition System. Journal of Systemics, Cybernetics and Informatics.
18. Patel, Chirag & Shah, D. & Patel, Atul. (2013). Automatic Number Plate Recognition System (ANPR): A Survey. International Journal of Computer Applications (IJCA). 69. 21-33. 10.5120/11871-7665. [CrossRef]
19. A. Kashyap, B. Suresh, A. Patil, S. Sharma and A. Jaiswal, "Automatic Number Plate Recognition," 2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), 2018, pp. 838-843, doi: 10.1109/ICACCCN.2018.8748287. [CrossRef]
20. Rai, Vanshika and Kamthania, Deepali, Automatic Number Plate Recognition (July 3, 2021). Proceedings of the International Conference on Innovative Computing & Communication (ICICC) 2021, Available at SSRN: https://ssrn.com/abstract=3879574 or http://dx.doi.org/10.2139/ssrn.3879574 [CrossRef]
21. Anish Lazrus, Siddhartha Choubey, G.R. Sinha, 2011. An Efficient Method of Vehicle Number Plate Detection and Recognition, International Journal Of Machine Intelligence, Volume 3, pp-134-13 [CrossRef]
22. Öztürk, Fikriye & Özen, Figen. (2012). A New License Plate Recognition System Based on Probabilistic Neural Networks. Procedia Technology. 1. 124–128. 10.1016/j.protcy.2012.02.024. [CrossRef]
23. Chandran, Saravanan. (2010). Color Image to Grayscale Image Conversion. 196 - 199. 10.1109/ICCEA.2010.192. [CrossRef]
24. Lim, Wei Hong. (2014). Illumination Estimation Based Color to Grayscale Conversion Algorithms.
25. Kornprobst, Pierre & Tumblin, Jack & Durand, Frédo. (2009). Bilateral Filtering: Theory and Applications. Foundations and Trends in Computer Graphics and Vision. 4. 1-74. 10.1561/0600000020. [CrossRef]
26. Said, K & Jambek, Asral. (2021). Analysis of Image Processing Using Morphological Erosion and Dilation. Journal of Physics: Conference Series. 2071. 012033. 10.1088/1742-6596/2071/1/012033. [CrossRef]
27. Thakur, Shilpa. (2015). Analysis of Sobel Edge Detection Technique for Face Recognition.
28. Dorothy, R & R M, Joany & Rathish, Joseph & Prabha, S & Rajendran, Susai & Joseph, St. (2015). Image enhancement by Histogram equalization. International Journal of Nano Corrosion Science and Engineering. 2. 21-30.
29. Patel, Omprakash & Maravi, Yogendra & Sharma, Sanjeev. (2013). A Comparative Study of Histogram Equalization Based Image Enhancement Techniques for Brightness Preservation and Contrast Enhancement. Signal & Image Processing : An International Journal. 4. 10.5121/sipij.2013.4502. [CrossRef]
30. Akbari Sekehravani, Ehsan & Babulak, Eduard & Masoodi, Mehdi. (2020). Implementing canny edge detection algorithm for noisy image. Bulletin of Electrical Engineering and Informatics. 9. 1404-1410. 10.11591/eei.v9i4.1837. [CrossRef]
31. Dimitrov, Darko & Holst, Mathias & Knauer, Christian & Kriegel, Klaus. (2008). Experimental Study of Bounding Box Algorithms. GRAPP 2008 - Proceedings of the 3rd International Conference on Computer Graphics Theory and Applications. 15-22.
32. Chaturvedi, P., Saxena, M., Sharma, B. (2019). A Bounding Box Approach for Performing Dynamic Optical Character Recognition in MATLAB. In: Rathore, V., Worring, M., Mishra, D., Joshi, A., Maheshwari, S. (eds) Emerging Trends in Expert Applications and Security. Advances in Intelligent Systems and Computing, vol 841. Springer, Singapore. https://doi.org/10.1007/978-981-13-2285-3_15 [CrossRef]

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