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Automatic Number Plate Recognition System using Template Matching and Euclidian Distance

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Abstract — **In the present world, the increase in the use of vehicles and automobiles are very useful for our day to day life. For the identification and classification of different vehicles according to the owner, vehicle type and region where the vehicle is used, we use the number plate. By the increase in the number of vehicles, the law enforcement and classification of vehicles are a great challenge to the authority. So the use of automatic number plate recognition system has a very important role in the current scenario. There are several types of research and methods are used to implement the recognition of numbers from the images such as optical character recognition (OCR) etc. But by using those methods there are several limitations for the identification of numbers and also classification of numbers with the characters which are in the same shape. Here we use a new method for the number plate recognition which done by the template matching by calculating the Euclidian distance between the current input and the template. We are also done some morphological operations on the input number plate image. By using this method, we got an 85% accuracy in the local images that we took in number plates having different dimensions and different background colours.**

Keywords — **Automatic number plate recognition, Optical character recognition, Euclidian distance and Template matching.**

I. Introduction

An automatic plate number recognition (APNR) is a system that automatically detects the Number plate based in a photo of the cars plate. It is used for the law enforcement and identifying the cars in a park, catching car thieves by tracing suspect plates back to forged documents and in an electronic toll-collection system. For each application, the complications and problems characteristics should be analyzed. For example the angle of the cameras and the quality of the images change from one application to another, some images can be blurry (especially motion blurry), or an object obscuring, such as dirt or fog, can be on plate. This project aims to simulate an automatic plate number recognition system and will evaluate different techniques of image enhancement to improve the character recognition. Finally the edge histogram, followed by connected component techniques were chosen and a MATLAB application was developed to demonstrate.

There are several researches and methods are used to implement the recognition of numbers from the images such as optical character recognition (OCR) etc. but by using that methods there are several limitations for the identification of numbers and also classification of numbers with the characters which are in same shape. Here we use a new method for the number plate recognition which done by the template matching by calculating the Euclidian distance between the current input and the template. We also done some morphological operations on the input number plate image. By using this method, we got an 85% accuracy in the local images that we took in number plates having different dimensions and different background colors.

II. Background and Significance

2.1 Introduction

In most cases, Number plate identification is a necessary procedure before Number plate Recognition. Methods to locate the Number plate region in images or videos from previous literature can be grouped into the following categories: Binary Image Processing, Gray-Level Processing, Color Processing and Classifiers [1]. Character segmentation is also a very important step before character identification. The methods for character segmentation can be combined into Binary Image Processing, Gray-Level Processing and Classifiers. To identify the segmented characters, there are a lot of algorithms using the pattern/template matching or learning based classification have been developed [2-4].

2.2 Number plate identification

2.2.1 Binary Image Processing

To select Number plate regions from background images, techniques based on combinations of edge statistics and morphology can get accurate outputs. In [5], they applied edge operators on a gray image after smoothing and normalization to extract horizontal and vertical edge maps. Statistical

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analysis of edges was then performed to detect the rectangle of license plate. The procedure was performed in a step by step manner at different scales. Several Number plate regions were left after this method. The final decision was made based on the connected component analysis (CCA).

They claimed that their algorithm can achieve 99.6% detection rate from 200 images. Many other Number plate detection algorithms [6, 7] also follow similar procedures. However, such methods are generally based on a hypothesis that the edges of the Number plate frames are clear and horizontal. If the Number plate frames were not clear or they had some bluer or distortion transformation, these algorithms may not produce required results.

2.2.2 Gray-Level Processing

The large difference between the back ground and the number characters is exploited in [8] to detect number plates with black characters over white backgrounds. While some other algorithms assumed that the density of edges in the Number plate region is larger than other regions if the contrast of the character and the Number plate is sufficiently large. For example, in [9, 10] they scanned the vehicle images with N-row distance to count the existent edges. Regions with high edge density will likely have the Number plate inside. Similarly, in [11], a block-based method was proposed, and blocks with high edge magnitude and variance are considered as the Number plate region.

For number plate detection Image transformation methods based on Hough transform, Gabor filters and wavelet transform have been applied. Hough transform is a classic algorithm to detect straight lines. Since the shape of Number plate can be defined by lines, [12] used the Hough transform to detect the end points of a number plate. This method is practical only when the background of the image is simple. Another drawback of this method is that the computational complexity of Hough transform is very high. Gabor filters are often used to check textures as they are sensitive to textures with different directions and scales. In 2003, F. Kahraman [13] et al. applied Gabor filters to detect Number plate and tested the algorithm with images acquired in a fixed angle and achieved a very good performance.

Vector quantization (VQ) is and another method used as a feature to encode images for Number plate detection [14]. In this method, number plate was separated into blocks and coded into strips. If a certain block contains high contrast region or details, it will split into four sub-blocks. In this case, the area of number plates with high contrast and complex texture will be represented by small blocks. By scanning the structure and the mean value of the blocks, the Number plate region can be easily located.

2.2.3 Color Processing

In many places, the number plate structure is strictly controlled. The color of the numbers and text and background is pre-defined, so that many algorithms use color information to detect Number plates [15, 16]. However, if the lighting conditions change, the color of the license plates will vary. So the Number plate detection algorithms that only rely on the color information may not achieve high identification rates. And for the countries like United States, since there are a large variety of license plates, such methods cannot be applied.

2.2.4 Classifiers

Currently, studying based Number plate detection methods using different classifiers become very popular. The general idea is to use a classifier to group the features extracted from the vehicle images into positive class (Number plate region) or negative class (non-number plate region). A number of computational intelligence architectures, such as artificial neural networks (ANNs), genetic programming (GP), and genetic algorithms (GAs), were implemented for license plates detection. However, such algorithms generally needed many parameters. And if the parameters were not tuned properly, they may not produce required results.

The discrete-time cellular neural networks (DTCNNs) was applied for Number plate detection in [17]. They extract two features of "grayness" and "texture" from the vehicle image, and used the DTCNNs to identify the pixels in the images with gray value in certain range and certain type of histogram after applying the Sobel operator.

Their framework distinguished over 85% tags. The beat coupled neural system (PCNN) was a novel neural system calculation and was generally utilized in sign and picture preparing fields. PCNN was connected to section Number plate hopefuls from vehicle pictures, before the Fourier change and a measurement procedure to find Number plate zone. This strategy accomplished a discovery rate of 85%.

The time-delay neural system (TDNN) was actualized by Kim et al. for Number plate discovery and accomplished astounding outcome. A TDNN is a multilayer feed-forward organize whose shrouded neurons and yield neurons are duplicated crosswise over time. They utilized two TDNNs as level and vertical channels to investigation the shading and surface data of the vehicle pictures. Their framework accomplished 97% exactness in recognition just as a rapid. .

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Another noteworthy Number plate recognition technique was executed dependent on the convolutional neural system (CNN). CNN have been broadly utilized for optical character acknowledgment (OCR) reason. In this article, they utilized the convolutional subsampling to concentrate highlight map, and a progressive way to deal with inquiry the content hopeful in tag. This technique accomplished a discovery rate of 98%.

AdaBoost was effectively utilized with Haar-like highlights in a "course" for face identification. Utilizing the course structure, the foundation district can be prohibited, as it were, from further preparing. It was equipped for handling pictures extremely quick with high recognition rates. The possibility of AdaBoost calculation is to join a gathering of frail classifiers to shape a more grounded classifier. It was exhibited that the preparation mistake of the solid classifier methodologies zero exponentially with the quantity of emphases. In the above technique was connected for Number plate recognition, and a discovery rate of 93.6% was accomplished. As they utilized the Haar-like highlights, their outcome was invariant to shading, light, size and position of the tags. So this calculation can be connected with complex foundation. Xiangrong et al. separated three arrangement of useful highlights for content and utilized AdaBoost to identify content from normal scenes. Their calculation can distinguish 97.2% of the noticeable content from their test set, a large number of which are obscured.

SVM has additionally been generally connected for article recognition as of late [30, 31]. SVM is an example grouping calculation which limits an upper bound on the speculation blunder, while different classifiers are attempting to limit the preparation mistake. Furthermore, it was tried that SVM can function admirably even in high dimensional space. Kim et al. embraced SVM to arrange the shading surface highlights pursued by a consistently versatile mean move (CAMShift) calculation so as to distinguish Number plate area. The discovery rate of their framework is 92.7% with a miss rate of 3.7%.

2.3 Character Segmentation

As some LPR calculations require the single character contribution, after Number plate identification, the preprocessing to portion the entire Number plate into patches containing single characters is regularly required. Any blunder made amid this procedure will likewise influence the last LPR result.2.3.1 Binary Image Processing

The most widely recognized and easiest path for character division is to perform level and vertical projections of the parallel Number plate picture. The thought is to ascertain the entirety of the double Number plate district along even and vertical bearing, and produce two vectors. The positions where the base qualities situate in the vectors are the spot to fragment the characters. The CCA can likewise be utilized for character division. In the associated part was set apart as a potential character dependent on the standard concerning the negligible zone, width and stature. What's more, sometimes, CCA was utilized related to numerical morphology or different strategies for character division.

The numerical morphology strategy was connected for character division and can manage genuinely corrupted pictures adaptively. The morphological diminishing, thickening and pruning calculations were connected to the paired Number plate picture. To look through the regular division focuses, the flat and vertical histogram projection was done trailed by a consolidating task.

Shape following and displaying was likewise used to do character division. A form following strategy known as "bug following" was executed to portion characters a shape-driven dynamic form model was proposed to take care of the plate character division issue. The variational walking calculation was utilized joined with an angle and-ebb and flow ward speed capacity to portion the precise limits of the characters. Shape closeness insights were utilized as criteria to stop the emphasis when the front looks like the preparation characters.

2.3.2 Classifiers

Markov irregular documented (MRF) and Hidden Markov Chains were additionally utilized in character division in pictures or recordings. Franc and Hlavac utilized the Hidden Markov Chains to demonstrate a stochastic connection between an info picture and comparing character division. Their technique required some earlier learning, for example, the quantity of characters. What's more, the characters ought to be divided with equivalent width.

2.4 Number Plate Recognition

2.4.1 Classifiers

Different multilayered neural systems have been utilized for Number plate acknowledgment., they creators utilized a discrete-time cell neural systems (DTCNN's) to remove four unique highlights (even projection, vertical projection, level associated part tally and vertical associated segment tally) and a customary multi-layer recognition organize (MLP) to do the characterization. A 98.5% acknowledgment rate was accounted for utilizing this strategy.

Chang et al. proposed a LPR technique utilizing self-arranging neural systems which had the option to deal with loud, disfigured, broken or inadequate

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characters in tags. The topological highlights of the information characters were first determined and contrasted and the pre-put away character layouts, which will be performed by oneself sorting out character acknowledgment method. A great 95.6% acknowledgment rate was accomplished over a huge informational collection.

Probabilistic neural systems (PNN) were generally connected in LPR. As these kinds of systems can be structured and prepared quickly. A surprising acknowledgment rate of 99.5% was distributed in 2005.

SVM-based LPR algorithms have been very popular recent years. Kim et al. used a SVM classifier to do LPR for Korean license plates and reported an average character recognition rate of 97.2%. Arth et al. extracted Haar-like features from license plates in video frames, and processed LPR with a SVM classifier. They also compared the classification results using with One Vs. All and tree-like structures of different testing sets.

2.4.1 Pattern/Template Matching

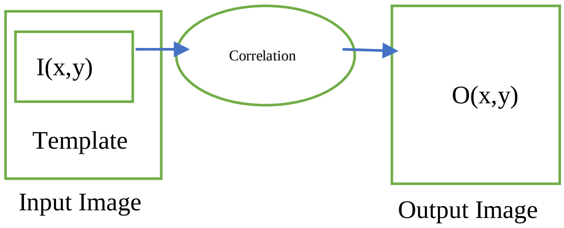
Format coordinating method was effectively actualized for LPR. They determined the separation of the fix from plate picture and the layout, and utilized classifier to locate the base separation to settle on a choice. The layout coordinating strategy was frequently joined with different strategies to do LPR.

2.5 Template Matching

Template matching is the Technique used in classifying objects. It compare portions of images against one another. For the template matching Sample image may be used to recognize similar objects in source image. If standard deviation of the template image compared to the source image is small enough, template matching may be used. The Templates are most often used to identify printed characters, numbers, and other small, simple objects. Here we are using the template matching technique for the matching of number plate characters and numbers with the standard templates.

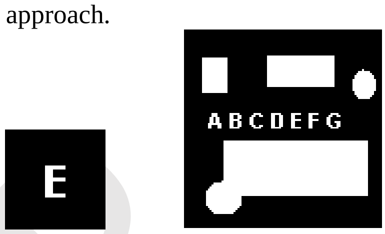
2.5.1 Method

The matching process moves the template image to all possible positions in a larger source image and computes a numerical index that indicates how well the template matches the image in that position. Match is done on a pixel-by-pixel basis.



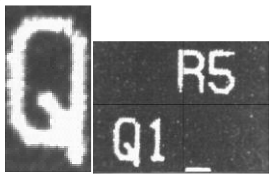
Bi-Level Image TM

Template is a small image, usually a bi-level image. Find template in source image, with a Yes/No approach.



Grey-Level Image TM

When using template-matching scheme on grey-level image it is unreasonable to expect a perfect match of the grey levels.
•Instead of yes/no match at each pixel, the difference in level should be used.



Euclidean Distance

Let *I* be a gray level image
and *g* be a gray-value template of size $n \times m$.

$$\boldsymbol{d(i, g.r.c)} = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{m} (\boldsymbol{I(r+i, c+j) - g(i,j)})^2}$$

In this formula *(r,c)* denotes the top left corner of template *g*.

2.5.2 Correlation

•Correlations a measure of the degree to which two variables agree, not necessary in actual value but in general behaviour.
•The two variables are the corresponding pixel values in two images, template and source.

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2.5.3 Grey-Level Correlation Formula

$$cor = \frac{\sum_{i=0}^{n-1}(xi - x1).(yi - y1)}{\sum_{i=0}^{n-1}(xi - x1)^{2.}\sum_{i=0}^{n-1}(yi - y1)^{2.}}$$

x is the template gray level image
x1 is the average grey level in the template image
y1 is the source image section
y is the average grey level in the source image
N is the number of pixels in the section image
(N= template image size = columns * rows)
The value cor is between –1 and +1, with larger values representing a stronger relationship between the two images.

III. LITERATURE REVIEW

In view of advanced background the amount plate image that images underneath the various illumination condition, during this analysis, Deng L. et al. (2017) projected one in body levels quick localization methodology. This methodology use variety plate pure mathematics characteristic, textural property further as color characteristic. first off it takes a way a lot of faster interleaved methodology of sampling consistent with the grey texture feature of the vehicle plate. Secondly, to get rid of the foremost of the background unrelated consistent with the pure mathematics feature of the vehicle plate. Thirdly, to calculate the grey statistics of the candidate space victimisation the tactic of consecutive scanning and also the color statistics, so it will get the correct center. Then the trump expands consistent with the central region for might contain the whole license plate's subgraph [18]. Prabhakar et al. (2017) conferred a powerful technique for localisation, segmentation and recognition of the characters inside the placed plate. pictures from still cameras or videos are obtained and regenerated in to grayscale images. Hough lines are determined victimisation Hough remodel and so the segmentation of gray scale image generated by finding edges for smoothing image is used to chop back the number of connected half and so connected part is calculated. Finally, single character inside the car place is detected [19]. Beibut et al. (2017) review alternative strategies ANd projected an formula for automatic variety plate recognition. a brief review is performed on the varied strategies of variety plate recognition algorithms [20]. Balamurugan et al. (2018) conferred a paper that deed the automated variety plate recognition system from the traffic police work video. The projected system detects the amount plate of a vehicle from video input and so performs the super resolution technique. Applying the Optical Character Recognition Technique it acquires the text from the super resolution image of auto variety plate by means that it compares with the RTO info and so it show the main points of the vehicle like homeowners name, vehicle registration etc [21]. Some of the prevailing algorithms supported the principle of learning takes plenty of your time and experience before delivering satisfactory results however even then lacks in accuracy. Karwal et al. (2018) developed AN economical methodology for recognition for Indian vehicle variety plates supported example matching. The formula used changed Otsu's methodology for threshold partitioning. Scale variance between the characters was reduced by increasing the correlation between the templates [22].

Yousef et al. (2018) conferred a straightforward, however quick and economical technique for automatic variety plate recognition (ANPR) victimisation SIFT (Scale Invariant Feature Transform) options. This technique is employed to mechanically find and acknowledge, as a special case, the Jordanian license plates. During this paper, SIFT-based example matching technique is employed to find special marks within the vehicle plate. Upon flourishing detection of these marks, the amount plate is metameric out from the initial image and OCR (Optical Character Recognition) is employed to acknowledge the characters or numbers from the plate [23]. Sathiyanarayanan et al. (2018) conferred time observance of vehicles victimisation motion detection, vehicle pursuit and variety (license) plate identification technique. The time observance method is obtaining advanced because of increase within the variety of vehicles within universities, colleges, corporations or faculties. The traffic flow at peak hours within the field, must be monitored in AN economical method. Therefore, to change this observance method, this paper detects the entry of vehicles victimisation motion detection technique. Then capture the front portion of the vehicle as a picture for preprocessing and segmentation. Finally, extracting the amount plate of the vehicle victimisation optical character recognition and log it together with the present timestamp for entry purpose [24].

Dewan et al. (2018) designed variety plate recognition system victimisation the hymenopteran colony optimization technique. Hymenopteran colony optimization technique serves higher ends up in edge detection whereas applying image segmentation, thus victimisation the thought in variety plate recognition guarantees higher accuracy. The hymenopteran colony optimisation (ACO) is an optimization formula impressed by the natural behavior of ant species that ants deposit secretion on the bottom for forage. ACO is

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introduced to grant a far better image edge detection. The projected ACO-based edge detection approach is ready to ascertain a secretion matrix that represents the sting data conferred at every constituent position of the image, consistent with the movements of variety of ants that are sent to maneuver on the image. What is more, the movements of those ants are driven by the native variation of the image's intensity values. Eventually, this offers the amount plate space extracted from the image with improved accuracy. Finally a personality recognition model is employed to grant out the ultimate vehicle number [24]. Nguwi et al. (2018) mentioned the importance of variety plate recognition and its corresponding application in several countries. Varied strategies for recognizing variety plates are reviewed. Most of the systems are able to deliver sensible recognition rate of higher than ninetieth. However, there's an absence of literature reportage variety plate recognition in pictures with reedy background. This paper projected a system that's able to tolerate background level up to twenty with recognition rate of eighty five. The system used a mix of filters and morphological transformation for segmenting the amount plate. It then uses resilient back-propagation neural networks for recognition. Ahmad et al. (2018) reviewed a collection of progressive ALPR strategies and, compared their several performances by testing them on an expensive info of vehicles from Ontario (Canada). Islam et al. (2018) conferred a technique to spot vehicle variety plates. The projected technique is constructed on morphological operations supported totally different structuring components so as to maximally exclude non-interested region and improve object space. This technique has been fully fledged employing an info of variety plates and simulated results demonstrate major enhancements as compared to alternative typical systems. The success rate of the projected methodology is concerning ninety two with varied light-weight conditions.

IV. PROPOSED METHODOLOGY

4.1 Flow of Proposed Research Work

The proposed method is designed for Vehicle Number plate Detection for Indian vehicles. In Figure 4.1 the method for proposed System is depicted. Rest of methodology is described in following subheadings.

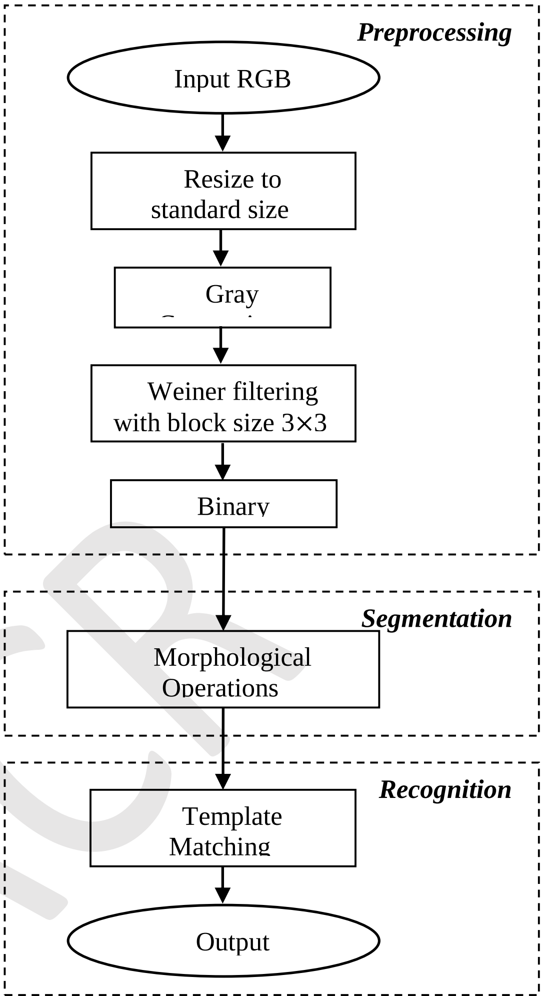

Figure 4.1: Flow diagram for proposed research work

4.2 Preprocessing

In this module firstly an input RGB image is taken from an external source such as database or camera which is converted to gray scale. Generally, the image obtained contains some irrelevant information or impurities such as holes, dirt particles and the background which must be removed. The noise is removed using filtering.

Following operations are performed in preprocessing phase:

A. Initially an RGB image is taken as input.

Figure 4.2: RGB input image

B. Resize to standard size (500×700 pixel)

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International Journal of Digital Application & Contemporary Research
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Figure 4.3: Resizing

C. Gray conversion of resized image

Figure 4.4: Gray conversion

D. Weiner filtering with block size 3×3

Figure 4.5: Filtered image

Wiener filtering is used to face the problems such as colour distortion while using dark channel prior when the images with large white area is being processed. Wiener filter also decreases the running time of algorithm.

E. Binary conversion

Figure 4.6: Binary image

4.3 Segmentation using Morphological Operations

Segmentation is part of the data reduction stage and involves the partitioning of the image plane into meaningful parts, such that “a correspondence is known to exist between images on the one hand and parts of the object on the other hand”

Binary Morphology

In binary morphology, everything could be defined using the set operations. Formally, let I and B are the sets corresponding to the image and structuring element, then

$$I = \{(x,y) \mid I[x,y] <> 0,\ \forall x,y \in I_R\} \tag{4.1}$$

where I_R is the set of all possible (row, column) elements over and image I. B can be defined in a similar manner.

There are two basic operations in morphology, which are called dilation and erosion.

The dilation of I by B is denoted by I⊕B and it is defined as

$$I \oplus B = \{c \mid c = i + b, \text{ where } i \in I, b \in B\} \tag{4.2}$$

In the mathematics literature, the dilation is also called as Minkowski addition to refer the inventor of the operator. To complete the dilation operation, B should be translated to the every image pixel and the union of the result should be taken as an overall result. Therefore, to be precise, translation of a set should be defined to shift the structuring element to a specific image point.

The translation of set B by t is defined as follows:

$$B_t = \{c \mid c = b + t,\ \forall b \in B\} \tag{4.3}$$

Dilation operation is defined as follows:

$$Dil(I,B) = \bigcup_{t \in I} I \oplus B_t \tag{4.4}$$

In the same sense, erosion and erosion operations are defined as in Equations 4.4, 4.6 respectively.

$$I \ominus B = \{c \mid c = i - b,\ i \in I,\ b \in B\} \tag{4.5}$$

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$$Ero(I,B)=\bigcap_{t\in I} I\Theta B_t \quad (4.6)$$

Figure 4.7: Perform morphological dilation with disk structure of radius 5 pixel

Figure 4.8: Perform morphological opening, remove white areas less than 40000 sq. pixel

Figure 4.9: Clear boundary white pixels

By using the primitive operations, several morphological operations can be defined. The two fundamental compound capacities that could be built by utilizing widening and disintegration are opening and shutting individually. The opening could be characterized as widening a picture in the wake of disintegrating. The end could be characterized as dissolving and picture subsequent to expanding.

These tasks could be comprehended by investigating the pragmatic significance of the fundamental activities. Since widening develops a set that is expansion of the umbrae of the picture and organizing component, it makes the high power portions of the picture develop, and in the comparable sense, disintegration makes them shrivel.

So when a picture is opened by an organizing component, it is first dissolved and a portion of the little dull territories vanish, at that point it is enlarged and some way or another the structures bigger than the organizing component are reestablished to their unique structure. As generally speaking procedures it is a smoothing task that evacuates the little parasitic zones and smoothes the article forms.The opening of a set I by structuring element B is defined as:

$$I \circ B = (I \ominus B) \oplus B \quad (4.7)$$

Similarly, the closing of a set I by structuring element B is defined as:

$$I \cdot B = (I \oplus B) \ominus B \quad (4.8)$$

Finally isolate objects in image reading line wise (left to right in each line). Resize each object to 150×100.

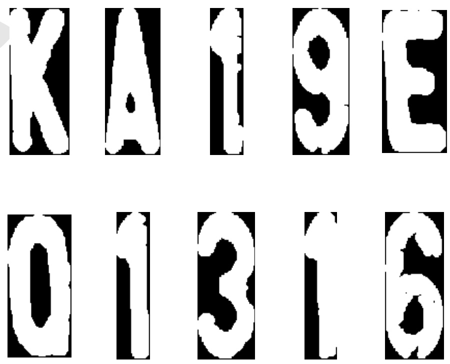

Figure 4.10: Object isolation

4.4 Recognition using Template Matching

In this module the named characters are recovered and perceived. The layouts stacked are resized to the measure of perceived characters. Standardized cross relationship layout coordinating is utilized to locate the best match. Formats from a current layout set are chosen and resized by the extent of the parts found all the while. Resizing is done so that the scale change is limited. In the proposed calculation, the tallness and width of the layout picture is resized to the stature and width of the characters of the handled picture. Standardized Cross Correlation is performed between the parts and the format picture to discover the level of comparability between them. The esteem is gotten is contrasted with a given edge. On the off chance that the estimation of cross

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connection is more prominent than the proposed edge, at that point the first edge esteem is refreshed to the upgraded one. In the event that more than one connection esteems surpass the past edge, at that point edge is refreshed to the most astounding among these qualities for the best match. The coordinated characters are recovered and the outcome is put away in a content record .

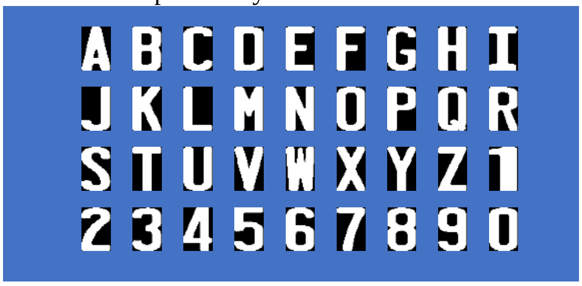

Figure 4.11: Perform template matching from this templates

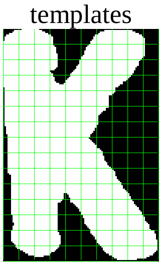

Figure 4.12: Divide each letter in blocks, block size (10×10), total blocks 150

Then, count number of white pixel in each block, total 150 value will be there, one for each block

	1	2	3	4	5	6	7	8	9	10
1	68	98	84	11	0	16	82	90	74	4
2	100	100	100	41	0	78	100	100	99	8
3	100	100	100	35	33	100	100	100	56	0
4	98	100	100	62	94	100	100	66	3	0
5	90	100	100	100	100	100	86	3	0	0
6	90	100	100	100	100	100	33	0	0	0
7	81	100	100	100	100	85	2	0	0	0
8	70	100	100	100	100	85	9	0	0	0
9	70	100	100	100	100	100	60	0	0	0
10	57	100	100	100	100	100	100	28	0	0
11	50	100	100	96	92	100	100	87	6	0
12	50	100	100	55	30	100	100	100	62	0
13	38	100	100	50	0	72	100	100	100	25
14	44	100	100	65	0	15	97	100	100	82
15	3	46	66	19	0	0	30	86	86	54

Figure 4.13: Number of white pixel in each block

Normalize Feature: Divide each value by maximum value in matrix and save it as a column vector.

	1	2	3	4	5	6	7	8	9	10
1	0.6800	0.9800	0.8400	0.1100	0	0.1600	0.8200	0.9000	0.7400	0.0400
2	1	1	1	0.4100	0	0.7800	1	1	0.9900	0.0800
3	1	1	1	0.3500	0.3300	1	1	1	0.5600	0
4	0.9800	1	1	0.6200	0.9400	1	1	0.6600	0.0300	0
5	0.9000	1	1	1	1	1	0.8600	0.0300	0	0
6	0.9000	1	1	1	1	1	0.3300	0	0	0
7	0.8100	1	1	1	1	0.8500	0.0200	0	0	0
8	0.7000	1	1	1	1	0.8500	0.0900	0	0	0
9	0.7000	1	1	1	1	1	0.6000	0	0	0
10	0.5700	1	1	1	1	1	1	0.2800	0	0
11	0.5000	1	1	0.9600	0.9200	1	1	0.8700	0.0600	0
12	0.5000	1	1	0.5500	0.3000	1	1	1	0.6200	0
13	0.3800	1	1	0.5000	0	0.7200	1	1	1	0.2500
14	0.4400	1	1	0.6500	0	0.1500	0.9700	1	1	0.8200
15	0.0300	0.4600	0.6600	0.1900	0	0	0.3000	0.8600	0.8600	0.5400

1	0.6800
2	1
3	1
4	0.9800
5	0.9000
6	0.9000
7	0.8100
8	0.7000
9	0.7000
10	0.5700
11	0.5000
12	0.5000
13	0.3800
14	0.4400
15	0.0300
16	0.9800
17	1
18	1
19	1
20	1
21	1
22	1

Figure 4.14: 150 values of normalized feature

Match with each of 36 templates using Euclidian distance.

In mathematics, a Euclidean distance matrix is an n×n matrix representing the spacing of a set of n points in space. According to the Euclidean distance formula, the distance between two points in the plane with coordinates (x, y) and (a, b) is given by:

$$dist\{(x, y), (a, b)\} = \sqrt{(x - a)^2 + (y - b)^2} \quad (4.9)$$

Minimum distance will be the matched one and finally figure 4.15 shows the recognized result.

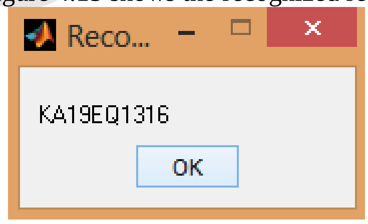

Figure 4.15: Recognized characters of number plate

V. CONCLUSION

Vehicle Number plate Recognition is a pattern recognition approach with great importance in vehicle counting, traffic surveillance and law enforcement. Consequently, number of algorithms have been proposed in recent times for efficient disposal of the application.

This research work presents Vehicle Number plate Recognition System based on morphological operations and template matching scale variance by using template matching with Normalized Cross Correlation. Simulation results show that the proposed approach successfully recognized the character of license plate.

REFERENCES

[1] C. N. E. Anagnostopoulos, I. E. Anagnostopoulos, I. D. Psoroulas, V. Loumos, and E. Kayafas, "Number plate recognition from still images and video sequences: a survey," Intelligent Transportation Systems, IEEE Transactions on, vol. 9, pp. 377-391, 2008.

[2] S. Yohimori, Y. Mitsukura, M. Fukumi, N. Akamatsu, and N. Pedrycz, "Number plate detection system by

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using threshold function and improved template matching method," in Fuzzy Information, 2004. Processing NAFIPS '04. IEEE Annual Meeting of the, 2004, pp. 357-362 Vol.1.

[3] Q. Jin, S. Quan, Y. Shi, and Z. Xue, "A fast Number plate segmentation and recognition method based on the modified template matching," in Image and Signal Processing, 2009. CISP '09. 2nd International Congress on, 2009, pp. 1-6.

[4] L. Xiaoping, L. Xiaoxing, W. Shuaizong, Z. Lin, L. Yinxiang, and D. Hongjian, "Research on the recognition algorithm of the Number plate character based on the multi-resolution template matching," in New Trends in Information Science and Service Science (NISS), 2010 4th International Conference on, 2010, pp. 341-344.

[5] B. Hongliang and L. Changping, "A hybrid Number plate extraction method based on edge statistics and morphology," in Proceedings of the Pattern Recognition, 17th International Conference on (ICPR'04) Volume 2 - Volume 02, 2004, pp. 831-834.

[6] D. Zheng, Y. Zhao, and J. Wang, "An efficient method of Number plate location," Pattern Recogn. Lett., vol. 26, pp. 2431-2438, 2005.

[7] P. V. Suryanarayana, S. K. Mitra, A. Banerjee, and A. K. Roy, "A morphology based approach for car Number plate extraction," in INDICON, 2005 Annual IEEE, 2005, pp. 24-27.

[8] P. Comelli, P. Ferragina, M. N. Granieri, and F. Stabile, "Optical recognition of motor vehicle license plates," Vehicular Technology, IEEE Transactions on, vol. 44, pp. 790-799, 1995.

[9] J. Cano and J.-C. Pérez-Cortés, Vehicle Number plate segmentation in natural images vol. 2652. Berlin, ALLEMAGNE: Springer, 2003.

[10] J. Barroso, E. L. Dagless, A. Rafael, and J. Bulas-Cruz, "Number plate reading using computer vision," in Industrial Electronics, 1997. ISIE '97., Proceedings of the IEEE International Symposium on, 1997, pp. 761-766 vol.3.

[11] L. Hsi-Jian, C. Si-Yuan, and W. Shen-Zheng, "Extraction and recognition of license plates of motorcycles and vehicles on highways," in Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on, 2004, pp. 356-359 Vol.4.

[12] V. Kamat and S. Ganesan, "An efficient implementation of the Hough transform for detecting vehicle license plates using DSP'S," in Proceedings of the Real-Time Technology and Applications Symposium, 1995, p. 58.

[13] Deng L, Song J.Y., "A Number Plate Recognition System for Abnormal Data", IEEE, 2nd International Conference on Future Generation Communication and Networking, Vol. 2, pp. 137-140, December 2008.

[14] Prabhakar P, Anupama P, Resmi SR., "Automatic vehicle number plate detection and recognition", International IEEE Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), pp. 185-190, July 2014.

[15] Beibut A, Magzhan K, Chingiz K., "Effective algorithms and methods for automatic number plate recognition", IEEE 8th International Conference on Application of Information and Communication Technologies (AICT), pp. 1-4, October 2014.

[16] Balamurugan G, Punniakodi S, Rajeswari K, Arulalan V., "Automatic number plate recognition system using super-resolution technique", International IEEE Conference on Computing and Communications Technologies (ICCCT), pp. 273-277, February 2015.

[17] Karwal H, Girdhar A., "Vehicle number plate detection system for Indian vehicles", IEEE International Conference on Computational Intelligence & Communication Technology (CICT), pp. 8-12, February 2015.

[18] Yousef KM, Al-Tabanjah M, Hudaib E, Ikrai M., "SIFT Based Automatic Number Plate Recognition", IEEE 6th International Conference on Information and Communication Systems (ICICS), pp. 124-129, April 2015.

[19] Sathiyanarayanan D, Shrihari S, Veeramuthu A., "A Novel Methodology for Vehicle Plate Localization, Segmentation, and Recognition for Real Scenario using Algorithms". International Conference on Communications and Signal Processing (ICCSP), pp. 1593-1597, April 2017.

[20] Dewan S, Bajaj S, Prakash S., "Using Ant's Colony Algorithm for Improved Segmentation for Number Plate Recognition", IEEE/ACIS 14th International Conference on Computer and Information Science (ICIS), pp. 313-318, July 2017.

[21] Nguwi YY, Lim W J., "Number Plate Recognition in Noisy Image", IEEE 8th International Congress on Image and Signal Processing (CISP), pp. 476-480, October 2018.

[22] Ahmad IS, Boufama B, Habashi P, Anderson W, Elamsy T., "Automatic Number plate Recognition: A Comparative Study", IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), pp. 635-640, December 2018.

[23] Islam R, Sharif KF, Biswas S., "Automatic Vehicle Number Plate Recognition using Structured Elements", IEEE Conference on Systems, Process and Control (ICSPC), pp. 44-48, December 2018.