International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:6, No:10, 2012

A Robust Diverged Localization and Recognition of License Registration Characters

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Abstract**—**Localization and Recognition of License registration characters from the moving vehicle is a computationally complex task in the field of machine vision and is of substantial interest because of its diverse applications such as cross border security, law enforcement and various other intelligent transportation applications. Previous research used the plate specific details such as aspect ratio, character style, color or dimensions of the plate in the complex task of plate localization. In this paper, license registration character is localized by Enhanced Weight based density map (EWBDM) method, which is independent of such constraints. In connection with our previous method, this paper proposes a method that relaxes constraints in lighting conditions, different fonts of character occurred in the plate and plates with hand-drawn characters in various aspect quotients. The robustness of this method is well suited for applications where the appearance of plates seems to be varied widely. Experimental results show that this approach is suited for recognizing license plates in different external environments.

Keywords**—**Character segmentation, Connectivity checking, Edge detection, Image analysis, license plate localization, license number recognition, Quality frame selection

I. Introduction

LICENSE plate recognition performs an imperative responsibility in several transportation applications. Recognizing the license plate of a vehicle from a natural image is a complicated process that involves the detection of the license plate and recognition of characters on the plate. Natural scenes give many multi classes and different types of poses from that localizing the license plate is the more challenging process. These types of issues are referred as coarse-to-fine strategy [1]. Most of the License Plate Recognition systems (LPRS) are suffered with lighting variation problem because it may not get the proper edge of the shape of interest in different lighting conditions. LPRS techniques differ in accordance with different types of applications. Many techniques have already been suggested by Park et. al. [2] and Hegt [3]. However, these systems are not viable in adaptation of variations in different aspect ratios of plate dimensions. Most of these techniques put a lot of constraints on the size and color of the plate, the size of the characters, position of the vehicle, stationary backgrounds and fixed illumination.

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None of the system is independent of position, rotation and scale invariant plate analysis. The primary objective of this work is to minimize the number of restrictions and produce a generalized solution for LPRS that is aptly suited for unrestricted dimensions of plates as well as relaxing different illuminations. The proposed system consists of the following phases of operations: In image acquisition and quality frame selection, a video camera attached to a frame grabber gives image sequences. From this sequence, the frame with best quality is taken by using support vector machines. Pre-processing phase converts selected image to gray level and it is used for edge detection process. License plate localization phase extracts license plate candidate regions from a complex scene using EWBDM that provides self-determining of aspect ratios of LPs. Connectivity checking is based on vertical-trace method that extracts LP characters with independent of variation of plate drawings. Segmentation is performed with constraint checking which avoids detection of special characters as license number. Thinning is a process to detect font independent LP numbers. The Gabor filters are used to extract features from the thinned characters in order to make them as position, rotation, and scale invariant patterns and then is fed into Hamming neural network to rapidly recognize the character patterns.

The organization of this paper is as follows: Section II summarizes the literature on the previous research. The proposed method for License plate recognition is illustrated Section III. Section IV illustrates License number recognition process and Experimental Results. Section V gives the concluding remarks on the work and future enhancements.

II. Review of Literature

License plates (LPs) have been localized by looking for rectangular LP edges in the image edge map. The prerequisite for this method is that the license plate should exhibit sharp rectangular edges. However, if the color of the car and the license plate are almost the same and the transition from car body to the LP is not very distinguishable; in that case the rectangular edges of the license plate will not be visible. Therefore LP localization using only the edge map is not very robust. In [4] color histograms were used to locate the license plate. This technique fails under different lighting conditions when the actual color of the LP differs from the color reflected by it. This problem was overcome by the use of a neural network to first classify the color. Still the system would fail when the color of the license plate is the same as other parts of the car, or produces a similar histogram. Plate specific parameters such as plate aspect ratio or even exact plate measurements are used to locate correct candidate region [5],

[6], [7], [8], [11]. This method would fail when the aspect ratios vary drastically as observed in Indian license plates. System [3] utilizes intelligence neural network to process the image and localize the license plate. Other methods in [2] that have been aimed at relaxing the constraints on the complexity of the images have been successful in achieving lesser false detection rates. But the system remains to be improved further. Thus many effective techniques have been proposed and claim to be able to work with other kinds of license plates without making any major design changes. But as elaborated above, license plate recognition requires an approach that is suited for a wide variation of plate parameters such as color, font size and style, plate dimensions, even different size of characters in the same plate, and some special symbols.

III. LPRS ALGORITHM

The vehicles' video sequence acquired by the camera is fed into the LPRS. The input sequence is first digitized into individual frames that have a resolution of 640 X 480 pixels. Quality Frame Selection (QFS) module selects an appropriate frame from the input video sequence and passes it to the pre-processing module.

An LPRS requires only image data contained in the actual license plate. The image pre-processing module removes unnecessary data and thus saves a large amount of processing time in order to do the localization. Edge detection module distinguishes all possible sharp edges in the image. The license plate region is characterized by a dense collection of edges formed due to the difference in intensity of the dark foreground and light background of the plate. In connection with our previous work [17], EWBDM highlights these regions of high edge density for diverse aspect ratio of plates. Besides that there are two important tasks involved in the license plate identification process, character segmentation and recognition. The final module verifies the characters by means of syntax checking procedures and produce accurate license number. Each of the above mentioned processes are discussed in detail.

A. Image acquisition and QFS

This module is responsible for acquiring image sequence from a video camera. The image acquisition system outputs a sequence of captured frames. The frame selection module picks the best frame from the input sequence and then precedes remaining operations. In the still camera capturing, there is a chance for producing a single image with smearing artifact. This type of blurring artifact affects the area of the LP and subsequent operation of LPRS. Since, the sequence of vehicle capturing is more robust than the still image acquiring. However, the video capturing process needs QFS operation because, capturing device produces 25-30 frames per second, in that, all vehicle images are not sharp enough and clear characters in their license plates. Thus, we present an effective scheme to appraise image feature by analyzing the frequency distribution of the vehicle image. This method is capable of differentiating clear and motion-blurred images. In order to boost the speed of QFS system, the bottom half of the input sequences are chosen for quality assessment. The frequency distribution of input image sequences is measured using Fourier transformation. Then, the transformed frequencies are segregated into low, medium, high components. From these sets, the feature descriptors (FD) are extracted, which consists of pairs of features from the input sequence. The first feature is the total spectrum power of an image and second one is the ratio of the medium component with other frequency power. These two sets of features are fed to the support vector machine to differentiate clear and motion blurred vehicle images. Fig. 1 shows clear and motion blurred images and their Fourier spectrums. Eq.1-2 describes the feature selection process.

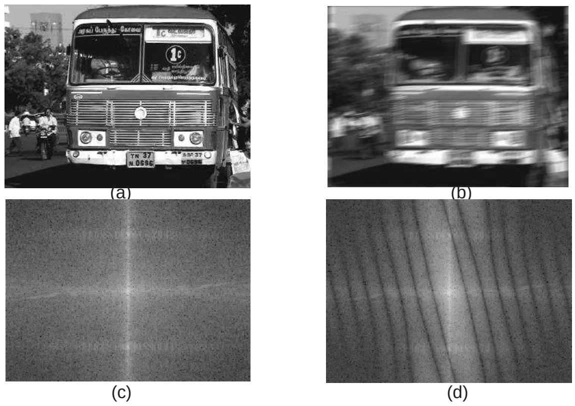

Fig. 1Fourier spectrums of clear and motion blurred images.

$$F(n,m)=\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y).e^{-j(2\pi/M)nx}.e^{-j(2\pi/N)my},$$

$$n=0,1,...M-1, m=0,1,...,N-1, \quad (1)$$

$$\Theta=(\phi_1+\phi_2+\phi_3, \phi_2/(\phi_1+\phi_3)), \quad (2)$$

where, $F(n,m)$ is the 2D discrete Fourier spectrum of a vehicle image, ϕ_1, ϕ_2 *and* ϕ_3 are the power of low, medium and high frequencies respectively. Support vector machine is trained to distinguish clear and motion blurred vehicle images. Here we assume each pattern x_k has been transformed to $y_k = \varphi(x_k)$, where $\varphi(.)$ is an appropriate nonlinear mapping. For each of the n patterns k =1, 2, 3,……., n, let z_k = +1 or -1, according to pattern k in class ω_1 or class ω_2. In this case, ω_1 and ω_2 are called features of clear (x_k) and motion blurred (x_l) images respectively. The separation of these two data sets belongs to the category of linear separable. This method separates data from these two categories by optimal hyper plane. There is some choice of weight, w and positive margin, b. The value of w and b should satisfy the condition as in Eq. 3 and such that equality is achieved on at least one point on each side of the hyper plane.

$$y_i(w.x_i+b)\geq 1, \quad (3)$$

where, x_i and y_i are the data set points, w is a weight and b is a positive margin for hyper plane.

Assume that x_k and x_l achieve equality and $y_k = 1$ and $y_l = -1$ respectively. It states that x_k is one side of the hyper plane, which represents clear image data and x_l is another side of the hyper plane that is motion blurred image. Clear and motion blurred images produce a compact and scatter clusters in the feature space, respectively.

B. Image Pre-Processing

The only relevant image data required for license plate recognition is the license plate of the subject vehicle. Eliminating unnecessary data greatly save time and boosts the efficiency of the system. This task is performed by gray conversion followed by edge detection. The image is processed in a bottom-up fashion, as the license plate tends to be in the lower areas of the image. In the perspective of image capturing, LP is occurred most of the sessions in the lower area of the image. If distance of the capturing is larger than the normal distance, then LP occurs at top portion of the image. Hence, lower area searching is enough and reduced entity searching in real time implementation. Thus input image is flipped vertically before further processing.

C. Gray-level conversion

The license plates are different types of background and foregrounds, for example, black background with white foreground license number. However, LP design specifications are not restricted in most of the countries as well as in order to generalize the LPRS the color independent is an essential task. This approach uses gray level pixel values for locating the LPs. This compensates for the change in shades of the colors caused by different lighting conditions. For example, at dusk white appears to have a slight red tinge. The gray image contains only essential data for the further phases of license plate recognition. In the conversion, RGB components transform by eliminating the hue and saturation information of chrominance components and retaining the luminance information of the lower half of the image.

D. Optimal Threshold Computation

Vehicle images are captured in different illuminations. Hence, there are many chances for producing false positives in locating LP. To avoid false detection, we adopt optimal threshold approach to choose the threshold values for edge detection process. This method based on approximation of the histogram of an image using weighted sum of two or more probability densities with normal distribution. The threshold is set as the closest gray-level corresponding to the minimum probability between the maximum of two or more distribution, which results in minimum error segmentation.

The algorithm of the optimal threshold method is as follows.

Step 1: There is no knowledge about the exact location of the vehicle object in the given image, hence, consider as an approximation that the four corner of the image contain background pixels and remainder contain vehicle objects.

Step 2: Compute μ_B and μ_F as the mean background and foreground of the gray-level, respectively. Threshold value is calculated as in Eqs.4-5.

$$\mu_B = \frac{1}{P*Q}\sum_{i=1}^{P}\sum_{j=1}^{Q} b(i,j), \mu_F = \frac{1}{N*M}\sum_{i=1}^{N}\sum_{j=1}^{M} f(i,j), \tag{4}$$

$$Thresh = \frac{|\mu_B + \mu_F|}{2}, \tag{5}$$

where P and Q are number of background pixels, N and M are number of foreground pixels. $b(i,j)$ and $f(i,j)$ are background and foreground information of the image, respectively.

Step 3: Minimum and Maximum of threshold values are chosen from Step 2.

E. Edge Detection

The LP localization process relies on edge information of the LP characters. Edge detection can be carried out by convolving the image with kernel masks like the Sobel filter mask. We propose an edge mapping process using the threshold method as

$$g(x, y) = a_{x,y} ,$$

$$e(a\ \ x, y) = \begin{cases} 0 & if\ 0 \le |a_{x-1,y} - a_{x,y}| \le LIT \\ 255 & if\ LIT < |a_{x-1,y}, y\ \ a_{x,y}| \le HIT \end{cases}, \tag{6}$$

Then, (e o g) is a composition function of g and e = h, from (x,y) to (0, 255) where g is a function from ordered pair to pixels in the image, e is a function from pixels to 0 or 255. $a_{x,y}$ denotes a set of pixel values in the gray level image. LIT and HIT are lower and higher intensity thresholds respectively. Applications with external illumination have different LIT and HIT threshold values observed from the optimal module. These values may change in application where lighting conditions vary drastically. This enables the system to compensate for varied lighting conditions i.e. time of day.

F. License plate localization

This process is critical to the success of any LP recognition system. Many techniques have been proposed for this task. Some techniques use the color of plate to detect it [4][12]. Most of the plate localization algorithm rely on plate specific properties such as looking for rectangles with standard aspect ratios [5],[6],[7],[11] of license plates or looking for edges that are equal to the standardized length or width of license plates[8]. These techniques cannot be adopted in countries where strict regulations on plate parameters have not been imposed. For example, Indian license plates exhibit a wide variation in their aspect ratios as shown in Fig 2.

The proposed method for LP localization involves two phases, in the first phase, the Extended Weight Based Density map method locates regions of high edge density and the coordinates of these rectangular regions are stored. Next, Constraints checking are performed to filter out the rectangular regions where the license plate is available. This method exploits the fact that, the edges are denser in the region containing the license plate than any other region of the image. To determine the concentration of edges the weight assignment scheme described in Eqs. (7) – (11) are applied.

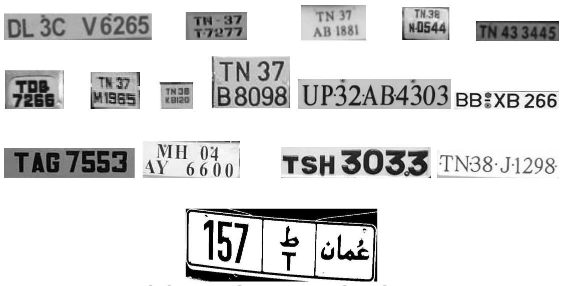

Fig. 2 Sample license plates captured on diverse scenario.

The weight allocation is done in a manner such that the degree by which the weight increases or decreases is directly proportional to the distance between current edge and next edge. Similarly the decrease in weight is directly proportional to the step size of each weight increment. This equation is derived as follows:
It can be stated that Weight decrement is directly proportional to $(i - p)$. Therefore,

$$EW_{t\_decr} \;\alpha\; (i - p) \quad \begin{cases} i - x_i & if \;\; i-p \le T \\ p - x_j & otherwise \end{cases} \tag{7}$$

Weight decrement is directly proportional to γ. Therefore,

$$EW\,t\_decr \;\alpha\; \gamma \tag{8}$$

From (7) and (8), we can derive

$$(i - p) = \partial\,\gamma \tag{9}$$

Where ∂ is decay constant. Therefore,

$$EW_t = \sum_{i=1}^{n} t_w (EW_t + (px_i)\gamma + (1 - px_i)(\partial\gamma(i - p))) \tag{10}$$

$$t_w = (((EW_t - |EW_t|)/-2EW_t)\beta) + (EW_t + |EW_t|)/2EW_t \tag{11}$$

Where n is the number of coordinate points, i is a coordinate of the current edge, p is a coordinate of the previous edge, γ is a Extended Weight increment factor, β is an initial weight and EW_{t_decr} is a weight decrement factor and EW_t is a weight value.
Algorithm of EWBDM is described as follows:

Step 1: Assign current pixel position $i = 1$ $EW_t = 0$

Step 2: if current pixel is 'ON' and $EW_t \le T$ then $EW_t = \beta$ otherwise $EW_t = EW_t + \gamma$

Step 3: if current pixel is 'OFF' and $EW_t > T$ then $EW_t = EW_t - \partial\gamma(i - p)$

Step 4: $i = i + 1$, Repeat step2 and step3 until $i \ge N$

EW_t represents the continuously varying weight of each row of the edge map and depends on the density of edges in the area under scrutiny. A raster scan begins at the beginning of every row of the edge map. When the first edge pixel (ON) is found, an initial weight of β is assigned to EW_t. This weight is then associated with the particular pixel and next pixel is investigated. If it is an edge pixel, the weight EW_t is incremented by the weight increment factor γ and then it is allocated to the current pixel. Also location of this pixel is stored in 'p' for use in the calculation of weight decay. If however the next pixel is OFF, then EW_t is decremented as shown in Step3. Notice, that the degree by which the weight W_t decays depends on both the decay constant ∂ as well as the distance between current pixel and most recently encountered edge. 'p' holds the location of most recent pixel and 'i' holds the location of current pixel. As a result, the weight decays at a much faster rate where edges are sparse as compared to regions of dense edges. This weight is then allocated to the current pixel. The procedure is repeated until all pixels in the current row have been exhausted. The process is repeated for all remaining rows of the edge map.

The peaks denote areas of concentrated edges. The areas of high edge density obtained in the EWBDM were compared to the corresponding areas in the input images and this approach arrived at a threshold value that can be used to extract the possible plate regions. The implementation of this scheme produced best results for the values $\partial = 0.03, \gamma = 3$ and $\beta = 7$. EWBDM is used to draw lines over areas of the image that interpreted as possible license plate regions, in other words lines are drawn over areas that contain text or text like entities. The coordinates of these lines are taken for finding exact location of the LP.

G. *Attain plate coordinates*

Once the extended weight based density map algorithm has been scanned the lower half of the image, coordinates are stored. It represents the regions in the image that may be part of the license plate. As stated earlier, the lines are drawn over all the text-like regions. This method has to examine the weight table and extract rectangular coordinates of the regions containing the text. Two methods are used for this purpose. The first method scrutinizes the table entries and groups together the lines whose X-coordinates are similar but Y-coordinates vary slightly. In other words, the lines of approximately equal length that vary only in their vertical component are grouped together. The extremity values (top left, bottom right) coordinates of each collective group of lines are stored in an entity descriptor table (EDT). Each of these extremity coordinate sets specifies a rectangular area where the text might be situated. The next method is used to make sure that the rectangular regions do not clip the characters in the license plate. It uses EDT as an input and takes each rectangular region into consideration and performs a column wise pixel scan near the left and right ends. If the extreme columns show a presence of more number of 'OFF' pixels, it means that the rectangular region has clipped part of a character. In this case, the column wise scan proceeds in the outward direction until the clipped character has been covered. Then the coordinates of the particular rectangle are modified and chosen for connectivity checking process.

IV. Character Segmentation & thinning

After deriving the possible plate coordinates, the plate portion is extracted from the input image then converted to bicolor model which makes the plate as a color independent. Hence it provides good results for the LPRS system in which the constraint of color occurrence in the LP is relaxed. A

International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:6, No:10, 2012

popular scheme for segmentation is the histogram method [4], [9] in which the characters are segmented in the region between two crests of the histogram. However, this scheme would fail if the characters on the license plate appear in two lines. Thus the proposed approach uses connectivity check algorithm and is supplemented with constraint checking. During connectivity checking, the size in terms of pixels and also the extremity coordinates of each connection of characters are recorded. The algorithm of connectivity check is described as follows:

Step 1: Converts the plate region into binary values that is text area transforms into 'ON' values and non-text area becomes 'OFF' values.

Step 2: Calculate the dimension of the plate and let M and N be the height and width of the plate, respectively. Assign minx = M, maxx = 1, miny = N and maxy=1. Raster scan begins from the top-left to bottom-left portion of the plate and find out ON values in the plate.

Step 3: If ON is found then assign minx = min(minx,x) and miny = Min(miny,y). Call searching process to check 8-way connectivity of pixels with constraint that the entire ON pixels lies with in the dimension of the plate.

Step 4: if ON value lies in the dimension of the plate and next connected pixel is also ON then assign, minx = min(minx,k), miny = min(miny,j), maxx = max(maxx,k), and maxy = max(maxy,j), where k, j is a new 'ON' pixel coordinates. Call search procedure recursively to fish all connected components in the plates. The visualization of connectivity results is illustrated in Fig 3.

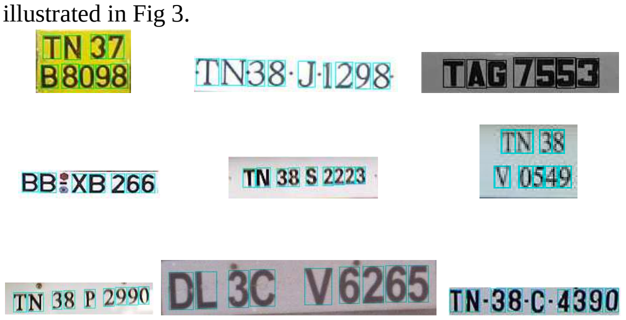

Fig. 3 The visualization of connectivity results

License plate characters may or may not be a machine-printed that could be drawn by artist. Hence, the handwritten issues arise in the LPRS. However, plates are machine-printed due to pan of camera capturing $\pm 20°$ angle variations occurred in the characters of the LP. In these plates, characters are not appeared in the straight horizontal lines; even characters height and width are also widely varied. If we start horizontal scanning then maximum height characters' pixel values are processed first and order of syntax is rapidly changed. Thus, vertical scanning is performed and segmented entire character in the LP area. If LP characters occur in two rows then the plate is implicitly subdivided by two and processed with connectivity checking of finding non-text area in the plate. In order to zero in on the rectangle that corresponds to actual plate, we check whether the blobs have dimensions similar to that of license plate characters. This acceptable range is derived from a field study of the various possible character sizes. This constraint checking process eliminates the chance of blobs occurring due to dust, black spots and other designs on the license plate to be classified as license plate characters.

A. Resizing and Thinning

After the segmentation, each characters of LP are converted into fixed rectangle of size 60*40 using bilinear transformation. License plate characters are different faces in font and size. In most of the countries, plates widely vary in different font of English characters. Hence, in order to make LPRS as a font independent, thinning is another important task, which transforms contour of the segmented characters to a set of thinned lines. These objects consist of topological structure of the characters that extracts the outer boundary of the character from the given contour objects. It removes unwanted pixels so that an object without holes thins to a minimally connected stroke, and an object with holes thins to a connected ring halfway between each hole and the outer boundary. The algorithm of the thinning is described as follows:

Step 1: Contour region points are assumed to have value 'ON' and background points to have values 'OFF'. It successive passes with two steps that a contour point is any pixel with value 'ON' and at least one 8-way neighbor value 'OFF'.

Step2: If number of ON of P1 range from 2 to 6 and total number of ON to OFF transitions is equal to 1 and AND (P2, P4, P6) = 0 and AND (P4, P6, P8) = 0 then pixel P1 is flagged for deletion to every border area of pixels in the contour.

Step 3: If number of ON pixels of P1 range from 2 to 6 and total number of ON to OFF transitions is equal to 1 and AND (P2, P4, P8) = 0 and AND (P2, P6, P8) = 0 then point P1 is flagged for deletion to other than border area of pixels in the contour.

Step 4: Repeat step 3 until no further points are deleted.

Fig. 4 shows the results of thinning algorithm applied to the various license characters.

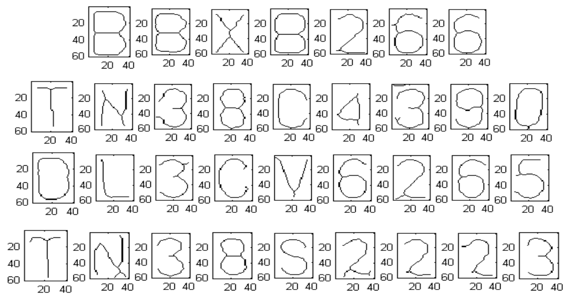

Fig. 4 The results of various license plate characters after applying thinning process

B. Two rows LP characters

The order of scanning makes the problem in two rows license plates. As mention early if raster scan starts in horizontal direction then the maximum height of 'ON' pixel is processed first which fails to fetch the character in the syntax ordering of the plate, to avoid this inconsistent we adopt for the vertical scanning approach. It vertically travels entire set of ON pixels and records rectangle connectivity of the characters. In the two rows LP as in Fig.5, character 'B' occurs little bit left away from the first row character 'T', which opens a chance for connectivity procedure to fetch 'B' as a first character of the LP instead of 'T'. In the vertical scanning operation, pixels are inspected from top to bottom manner and fetched entire components perfectly but the syntax of the LP is completely collapsed as in Fig.5a. Hence, we implicitly decompose the plate by two with constraint of non-text area and then process by the connectivity check procedure. This approach reduces the overburden to the syntax checking operations. Fig.5b. depicts the results of decomposition operation.

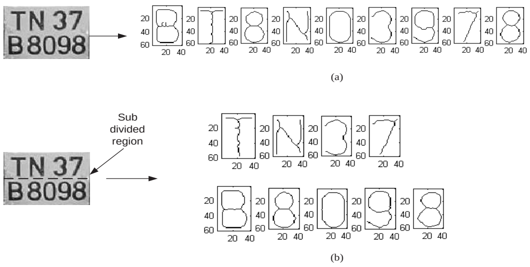

Fig. 5 Two rows LP characters and their related problems

V. LICENSE NUMBER RECOGNITION AND RESULT ANALYSIS

Typically template matching is the method of choice in most of the license plate recognition as in [3], [4], [9], [12] Template matching was experimented with initially, but due to wide variation of character font, the results were not satisfactory. Vehicle images may acquire in different pan and tilt conditions according to the fixing of camera or position of the vehicle. Hence, template matching with specific set of characters is not provided robust result in widely varying character fonts, degree of capturing and external environments. Thus, we choose the position, rotation, scale invariant Gabor filter that provides better result in texture analysis. First, we perform decay operation on the segmented images, that is, segmented character image is divided into 3 sub images as shown in Fig. 6. Most of the alphanumeric characters middle portion of the image provides efficient deviation of strokes and top/ bottom portions have arcs of the characters. Hence, we split the images into top, middle and bottom segments.

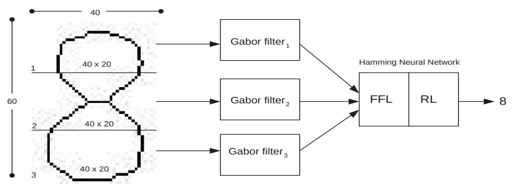

Fig. 6 Stages of LP number recognition using Gabor features and HNN

A. Character Feature Extraction

Each segmented portion is convoluted by Gabor spatial kernel. Gabor elementary functions are Gaussian function modulated by oriented complex sinusoidal functions. The complex function G(x, y) can be split into two parts, the even and odd filters. G_e (x, y) and G_o(x ,y), which are also known as the symmetric and anti-symmetric filters respectively.

Step 1: Image is divided into 3 sub images, each has 40*20 in height * width.

Step 2: Image pixels are converted to bipolar patterns.

Step 3: The central frequency of Gabor filter is ranged from 2 to 32 degrees and incremented by its power. Orientation angle (θ) is ranged from 0^o to 90^o incremented by 45^o.

Step 4: Total of 15 kernels are used to convolute each sub images, therefore, 45 features are extracted from each character image. The convolution operation is done by polynomial multiplication as

$$CharF(x,y) = \sum_{k=-1}^{1} \sum_{j=-1}^{1} G(j,k) I(x-j, y-k). \tag{13}$$

where G(j,k) is a Gabor Kernel and I(x,y) is a segmented character strip. Mean value of character strip has been calculated by changing frequency and orientation values. This is performed as

$$\bar{x} = \frac{1}{N * M} \sum_{i=1}^{N} \sum_{j=1}^{M} CharF\ (x_i, y_j). \tag{14}$$

where N, M is the size of the image and $\bar{x}$ is a character feature code.

Implementation has been done in VC++ and MATLAB. The efficiency of the proposed system has been tested with a wide variety of input images. The images were taken from various environments under different illumination.

B. Distance and angle of image capturing

We collected a sample database of images for testing the system to effectively measure the accuracy of the system from real time video sequences. The system was finally tested with a number of image sequences. Vehicle images have been captured in different pan and tilt of the camera viewing positions. The pan perspective projection of the vehicle images range from –20 to +20 degrees and aerial viewing positions range from 0 to 20 degrees. This system is robust for pan angle variations between -25 and +25 degrees and aerial view 0 to 25 degrees. Perspective angles below or above ±30 degrees cause the problems in character segmentation, as the symbols give the impression of joined or smashed.

C. False matches plates

The clarity of symbols in the license plate determines the accuracy of the segmentation module. If the symbols have space of at least one pixel width in between, they can be segmented efficiently. However, this is not always the case in India. In some plates, the symbols are smudged together or other foreign materials may partially occlude the plate. External illumination or points of light sources provide misdetection of license number in the vehicle image.

D.Ambiguity of Characters

The crucial aim of the feature extraction module is to avoid false positives in character recognition process. A common problem in license number recognition was as mentioned in [12], characters 'O' and 'D' or '5' and 'S' or 'B' and '8' provide ambiguous results. To resolve these problems, Gabor filter was used to extract feature from the character set which produces shift, rotation and scale independent features. Variations of feature in the ambiguous characters are given in Table I. These features were trained and tested by Hamming neural network to get maximum score of the characters.

TABLE I
AMBIGUITY CHARACTERS FEATURE VALUES

Character	Mean	Average absolute deviat	Standard deviat
O	38.7053	66.713734	8.162033
D	34.492	58.452563	7.523435
8	41.8455	69.240437	8.305075
B	49.3562	82.584942	9.06252
S	30.7827	52.422298	7.238064
5	34.2629	56.897289	7.540439

VI. CONCLUSION

In this paper, we have proposed and examined a new methodology for license plate recognition. The proposed methodology succeeds in relaxing a number of constraints like the distance between the vehicle and camera, the color, opacity factor of the license plate, the fonts of the license plate characters etc. QFS is proposed to select a moderate vehicle frame from the captured image sequences that can also be applied to any application like surveillance of natural images. EWBDM performs efficient operation in detecting text-like entities over the edges of the given image. It can localize the license plate in accordance with independent of its color that can also be extended to OCR applications to isolate text and non-text areas. Connectivity checking module is performed to segment characters in widely vary aspect quotients and is ably suited to recognize n rows license number plates which can also be extended to any document analysis. The position, rotation and scale invariant feature extractor is used to gather the features of character from the segmented templates, which avoids false positives in recognize process. Hence, the common problems of the shift of pixels, slant variations, size of contour and catastrophic of character pixels are resolved and provided best result in worst case analysis. The recognition rates in various conditions have been studied and have been illustrated in the paper. The proposed methodology has been found to show high recognition rates and quite suitable for conditions where a wide variety of license plates are to be dealt with. Future work in this area can concentrate on extending this methodology to extract and recognize multiple plates from the same image. It will require more processing time to localize one or more plates appeared in the image that could be reduced by incorporating parallel algorithms in the extended weight calculation phase.

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