Automatic multistyle licensed plate detection by using fuzzy logic classifier

J. Layolin sobiya
M.E, Applied Electronics
Sri Muthukumaran institute of technology,
Chennai, Tamilnadu

Mrs. P.Angelin priya
Assistant Professor, Dept of ECE
Sri Muthukumaran institute of technology
Chennai, Tamilnadu

Abstract: Automatic Number Plate Recognition is a mass surveillance system that captures the image of vehicles and recognizes their licence number. ANPR can be used in many applications, such as electronic payment systems (toll payment, parking fee payment), freeway, arterial monitoring systems for traffic surveillance and detection of stolen vehicles. In previous studies, there are so many methodologies were proposed to resolve the following challenges (location quantity, size, colour, font, occlusion, inclination etc) in extracting information from the captured image but every algorithm has their own draw back between accuracy of detection and processing speed. In the proposed multistyle detection method uses the fuzzy logic classifiers which help to identify the plate and characters with better accuracy and processing speed.

Index terms: Plate detection, Character extraction and recognition, Adaptation threshold, Neural Networks, Filtering, Multiresolution.

I.INTRODUCTION

Automatic license plate recognition (ALPR) plays an important role in numerous real-lifeapplications, suchas automatic toll collection, traffic law enforcement, parking lot access control, and road traffic monitoring [1]. ALPR recognizes a vehicle’s license plate number from an image or images taken by either a colour, black and white, or infrared camera. It is fulfilled by the combination of a lot of techniques, such as object detection, image processing, and pattern recognition. ALPR is also known as automatic vehicle identification, car plate recognition, automatic number plate recognition, and optical character recognition (OCR) for cars. Colour feature and texture feature are combined in [2], fuzzy rules are used to extract texture featureand yellow colours. The yellow colour values, obtained from sample images, are used to train the fuzzy classifier of the colour feature. The fuzzy classifier of the texture is trained based on the colour change between characters and license plate background. For any input image, each pixel is classified if it belongs to the license plate based on the generated fuzzy rules. Fuzzy logic has two different meanings. In a narrow sense, fuzzy logic is a logical system, which is an extension of multivalued logic. However, in a wider sense fuzzy logic (FL) is almost synonymous with the theory of fuzzy sets, a theory which relates to classes of objects with unsharp boundaries in which membership is a matter of degree. In this perspective, fuzzy logic in its narrow sense is a branch of FL. Even in its more narrow definition, fuzzy logic differs both in concept and substance from traditional multivalued logical systems. Another basic concept in FL, which plays a central role in most of its applications, is that of a fuzzy if-then rule or, simply, fuzzy rule. Although rule-based systems have a long history of use in Artificial Intelligence (AI), what is missing in such systems is a mechanism for dealing with fuzzy consequents and fuzzy antecedents. In fuzzy logic, this mechanism is provided by the calculus of fuzzy rules. The calculus of fuzzy rules serves as a basis for what might be called the Fuzzy Dependency and Command Language (FDCL). Intelligent Transportation Systems (ITS) are having a wide impact in people’s life as their scope is to improvetransportation safety and mobility and to enhance productivity through the use of advanced technologies [4].A special area inside the it’s are the Automatic Target Recognition (ATR) systems. The main goal of an ATR system is to detect, to classify and to recognize an object inside a scene. Inside this field, the automatic License Plate Recognition (LPR) systems are located. LPR is required for the purposes of enforcement, bordersurveillance, vehicle thefts, automatic toll collection and perhaps traffic control. In any automatic plate recognition system, two main different stages can be distinguished; first, a particular region within the input image has to be identified as a car plate (localization), and then a character sequence inside the region has to be validated as a correct plate string following somegrammatical rules (character recognition) [6]. These stages are always applied on controlled environments, static backgrounds or controlled light scenes [8], [9]. Under uncontrolled conditions, the process of detection should face a variety of situations like locating plates at different distances, different plate orientations, light conditions and noisy plate images. By these conditions, some characters are hardly recognizable or distinguishable fromothers.

The rest of this paper is organized as follows. Section II introduces the Existing system; Section III Proposed system. Next, Section IV evaluates the performance in area overhead, timing penalty, and throughput and reliability analysis to demonstrate the feasibility of the proposed architecture for Pattern matching applications. Conclusions are finally drawn in Section V.

II.EXISTING SYSTEM

A.LICENSE PLATE EXTRACTION

a) License Plate Extraction Using GlobalImage

Information Connected component analysis (CCA) is an important technique in binary image processing .It scans a binary image and labels its pixels into components based on pixel connectivity. Spatial measurements, such as area and aspect ratio, are commonly used for license plate extraction. The correct extraction rate and false alarms are 96.62% and 1.77%, respectively, by using more than 4 h of video.The connectedobjects that have the same geometrical features as the plate are chosen to be candidates. This algorithm can fail in the case of bad quality images, which results in distorted contours. The 2-D cross correlation with a prestored license plate template is performed through the entire image to locate the most likely license plate area. Extracting license plates using correlation with a template is independent of the license plate position in the image. However, the 2-D cross correlation istime consuming.

b) License Plate Extraction Using Character Features

License plate extraction methods based on locating its characters have also been proposed. These methods examine the image for the presence of characters. If the characters are found, their region is extracted as the license plate region. In [11], instead of using properties of the license plate directly, the algorithm tries to find all character-like regions in the image. This is achieved by using a region-based approach. Regions are enumerated and classified using a neural network. If a linear combination of character-like regions is found, the Presence of a whole license plate is assumed. The approach used in [15] is to horizontally scan the image, looking for repeating contrast changes on a scale of 15 pixels or more. It assumes that the contrast between the characters and the background is sufficiently good and there are at least three to four characters whose minimum vertical size is 15 pixels. A differential gradient edge detection approach is made and 99% accuracy was achieved in outdoor conditions. In [17], binary objects that have the same aspect ratio as characters and more than 30 pixels are labelled. The Hough transform is applied on the upper side of these labelled objects to detect straight lines. The same happens on the lower part of these connected objects. If two straight lines are parallel within a certain range and the number of the connected objects between them is similar to the characters, the area between them is considered as the license plate area.

B. LICENSE PLATE SEGMENTATION

a) License Plate Segmentation Using Pixel Connectivity

Segmentation is performed by labelling the connected pixels in the binary license plate image. The labelled pixels are analysed and those which have the same size and aspect ratio of the characters are considered as license plate characters. This method fails to extract all the characters when there are joined or broken characters.

b) License Plate Segmentation Using Projection Profiles

Since characters and license plate backgrounds have different colours, they have opposite binary values in the binary image. The binary extracted license plate vertically to determine the starting and the ending positions of the characters, and then project the extracted characters horizontally to extract each character alone. In [15], along with noise removal and character sequence analysis, vertical projection is used to extract the characters. By examining more than 30 000 images, this method reached the accuracy rate of 99.2% with a 10–20 ms processing speed. By reviewing the literature, it is evident that the method that exploits vertical and horizontal projections of the pixels is the most common and simplest one. The pro of the projection method is that the extraction of characters is independent of their positions. The license plate can be slightly rotated.

C. CHARACTER RECOGNITION

a) Character Recognition Using Raw Data

Template matching is a simple and straightforward method in recognition. The similarity between a character and the templates is measured. The template that is the most similar to the character is recognized as the target. Most template matching methods use binary images because the grey-scale is changed due to any change in the lighting.

Several similarity measuring techniques are defined in the literature. Some of them are Mahalanobis distance and the Bayes decision technique, Jaccard value, and the Hamming distance Character recognition uses normalizedcross correlation to match the extracted characters with the templates. Each template scans the character column by column to calculate the normalized cross correlation. The template with the maximum value is the most similar one. Template matching is useful for recognizing single-font, nonrotated, nonbroken, and fixed-size characters. If a character is different from the template due to any font change, rotation, or noise, the template matching produces incorrect recognition.

b) Character Recognition Using Extracted Features

Since all character pixels do not have the same importance in distinguishing the character, a feature extraction technique that extracts some features from the character is a good alternative to the grey-level template matching technique. It reduces the processing time for template matching because not all pixels are involved. It also overcomes template matching problems if the features are strong enough to distinguishcharacters under any distortion .The extracted features form a feature vector which is compared with the pre-stored feature vectors to measure the similarity. The feature vector is generated byprojecting the binary character horizontally and vertically. The feature vector is generated from the Hotelling transform of each character. The Hotelling transform is very sensitive to the segmentation result. In [17], the feature vector is generated by dividing the binary character into blocks of 3×3 pixels. Then, the number of black pixels in each block is counted. In [19], the feature vector is generated by dividing the binary character after a thinning operation into 3 × 3 blocks and counting the number of elements that have 0°, 45°, 90°, and 135° inclination. The character is scanned along a central axis. This central axis is the connection between the upper bound horizontal central moment and lower bound horizontal central moment.

III.PROPOSED SYSTEM

A. Car Plate Detection

As the input we have a digital image of a car; then, the plate is searched in the image. Essentially, the methodology to detect the plate is composed of two methods: detection of a rectangle,corresponding to the perimeter of the image of the license plate and by comparison of the normalized correlationcoefficient (match).

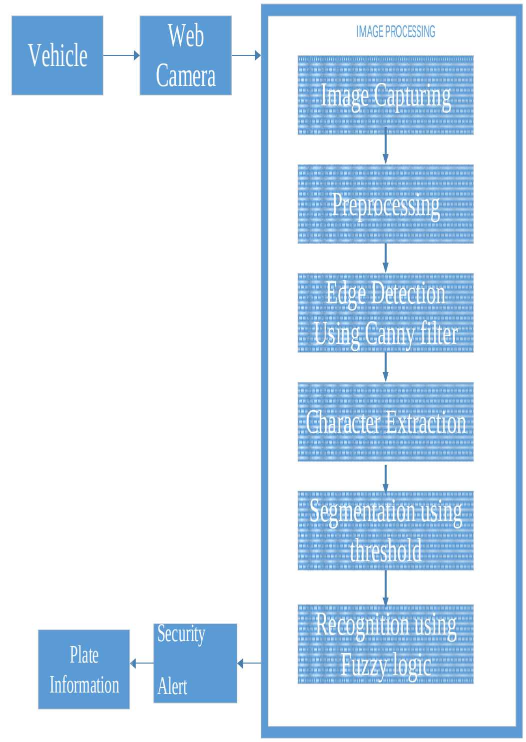


Fig.1 Proposed Flow Diagram

B. PREPROCESSING

Preprocessing is mainly used to enhance the processing speed, improve the contrast of the image, and to reduce the noise in the image. We firstly converts RGB image to gray scale image.RGB images to gray scale conversion is done by eliminating the hue and saturation information while retaining the luminance. To convert RGB values to gray scale values we formulated it by forming a weighted sum of the *R*, *G*, and *B* components:

$$Gray = 0.2989 * R + 0.5870 * G + 0.1140 * B$$

After it, we have to adjust the intensity of the image and reducing the contrast in the image. The technique used for intensity adjustment is known as histogram equalization. Histogram equalization enhances the contrast of images by transforming the values in an intensity image, or the values in the colour map of an indexed image, so that the histogram of the output image approximately matches a specified histogram.

Pseudo code to convert an image to a grayscale:

STEP1: Load the image
STEP2: Retrieve the properties of image like width, height and n channels
STEP3: Get the pointer to access image data

STEP4: For each height and for each width of the image, convert image to grayscale by calculating average of r,g,b channels of the image convert to grayscale manually
STEP5: Display the image after converting to grayscale

The flowchart shown in the following figure describes the algorithm to convert an image to gray scale image. Where brightness changes sharply. This change is measured by derivative in1D.For biggest change derivative has max value (or) second derivative is zero. The detection of edge is mostimportant as the success of higher level processing relies heavily on good edges.
Gray level images contain an enormous amount of data, much of which is irrelevant. The general edge detection involves three steps: filtering, differentiation and detection. In the first stage, the image is passed through a filter in order to remove the noise. The differentiation stage highlights the locations in the image where intensity changes are significant.

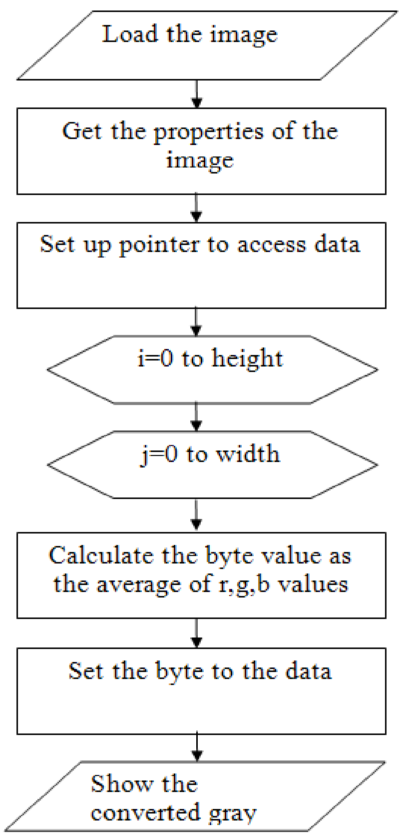


Fig.2 Convert an image to a greyscale

In the detection stage, those points where the intensity changes are significant are localized.

a)

b)

Fig. 3 a) Input jpg image b) Gray scale image

C. EDGE DETECTION

The edge detection technique called canny method based on Gaussian filter is applied in this task to find the edges of image. This technique also controls the resolution of the edges of image and reduces noise as well. Such detection technique provides the best result in detection of edge of image that has less difference in colour compared to other techniques. As a result the steps in preprocessing are reduced. Canny method consists of four steps as followings;

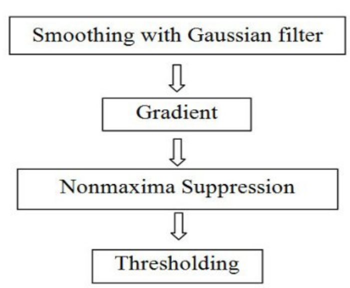


Fig.4 Workflow of Canny edge detection

The Canny edge detector is based on computing the squared gradient magnitude. Local maxima of the gradient magnitude that are above some threshold are then identified as edges. This threshold local peak detection method is called non-maximum suppression, or NMS. The motivation for Canny's edge operator was to derive an "optimal" operator in the sense that minimizes the probability of multiply detecting an edge, minimizes the probability of failing to detect an edge and minimizes the distance of the reported edge from the true edge. The first two of these criteria address the issue of detection, that is, given that an edge is present will the edge detector find that edge (and no other edges).

The third criterion addresses the issue of localization that is how accurately the position of an edge is reported. There is a trade-off between detection and localization -- the more accurate the detector the less accurate the localization and vice-versa. The objective function was designed to achieve the following optimization constraints:

1. Maximize the signal to noise ratio to give perfect detection. This favours the marking of true positives.

2. Achieve perfect localization to accurately mark edges.3. Minimize the number of responses to a single edge. This favours the identification of true negatives, that is, non-edges are not marked.

These criteria seem to be reasonable candidates for filters comparison. A system to use the canny edge detector in remote sensing image enhancement is proposed. First, Gaussian filter was used to perform image smoothing. Then, the sharp edge map produced by implemented canny edge detector is added to the smoothed noisy image to generate the enhanced image. The application of this technique is applied on a real remote sensing image.

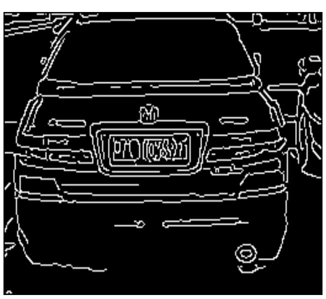


Fig .5 Canny edge detection

IV. DISCUSSION AND CONCLUSION

Standard edge detectors methods failed to perform adequately in such applications due to the noisy nature of remotely sensed data. Neither the Roberts Cross, the Sobel operator, nor Prewitt operator are able to detect the edges of the object while removing all the noise in the image. Since image enhancement (sharpening and de-noising) using canny edge detector, it is quite susceptible to noise, particularly if the standard deviation of the smoothing Gaussian is small. Thus it is common to see many spurious edges detected away from any Obvious edges.

One solution to this is to increase the smoothing of the Gaussian to preserve only strong edges. The implemented Canny edge detector presented the best performance both visually and quantitatively based on the measures such as mean square distance, error edge map and signal to noise ratio. The Gaussian smoothing in the canny edge detector fulfils two purposes: first it can be used to control the amount of detail that appears in the edge image and second, it can be used to suppress noise. Using the implemented canny edge detector as an enhancement tool for remote sensing images, the result was robust and achieved a very high enhancement level.

a) Rectangle detection

In order to detect a rectangle inside the car scene, we performed the following steps: 1) Minimum Filter, 2) Gaussian Pyramidal Filter

Minimum filter. We applied a minimum filter in order to assign to each pixel of the image, the minimum valueextracted from all the values contained inside an *n x n* mask. The goal is to decrease the contrast of the input image. The Gaussian mask used is *A/16*, where *A = Gaussian Kernel*. The weights pertaining to the mask have the shape of a Gauss bell described by means of equation 1, after this operation we convolve the input image using the equation

$$f(x,y) = e^{\frac{-x^2+y^2}{s^2}} \quad ....(1)$$

The results obtained are showed on figure 1. Figure 1 a) is the original image and figure 1 b) is the resulting image, at this image the contrast of the plate is enhanced and the character inside the plate are prepared for the stage of recognition.

a)

b)

Fig. 1 filtering. a) Original image and b) minimum filter results.

Gaussian Pyramidal Filter. This filter was applied to minimize the noise inside the image. Each level of theGaussian pyramid is smoothed by a symmetric kernel and down sampled to obtain the next level of the pyramid as shown in equation

$$P_{Gaussian}(I)^{j-1} = S \downarrow (G_{\sigma} P_{Gaussian}(I)) \qquad \text{....................} (3)$$

The set of images obtained correspond to the multiresolution representation of an image.

The results obtained are shown in figure 2. The images were obtained by means of down sampling and up sampling operations on the input image.

a)

b)

Fig. 2 Results obtained with Gaussian pyramid. a) Down sampling and b) up sampling.

b) Normalized correlation coefficient**.** WxH is the input image and a template size of wxh. Then the resulting image have W - w + 1 x H - h + 1 pixels. The value of a pixel at each location xy defines the similarity between the template and a rectangle inside an image with the upper left corner located at xy and the lower right corner located at $x + w - 1$, $y + h - 1$ As a result of this process we obtain a point inside the image which is the similar place to the pattern model defined. The results obtained are shown in figure 3.

Fig .3 results obtained with normalized correlation coefficient.

ROI thresholding. We need to perform the operation of thresholding inside the ROI detected which represent the plate. This operation is to detect the characters inside the ROI. In figure 10 we present the results obtained by thresholding the ROIs.

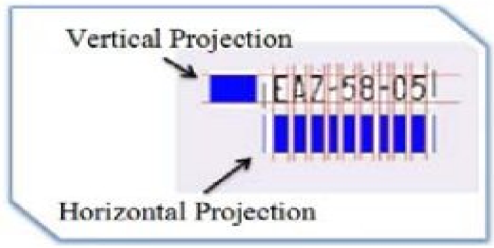
Fig .4 a) ROIs detected and b) the result of thresholding the ROIs detected.

B. Character Extraction

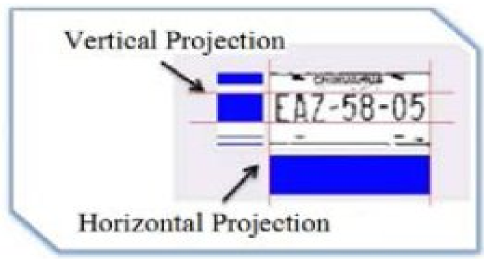
To detect and separate the characters we used horizontal and vertical projections, and an operation to normalize the size of a character.

a) Horizontal and vertical projections

The operation of the projection is to compute the quantity of pixels pertaining to each row for the case of vertical projection, and the quantity of pixels contained at columns for the case of horizontal projection. The minimum number of pixels in different vectors allows us to segment the characters contained in the plate. With this operation we obtain a square which enclose each character inside the image. The results obtained are shown in figure 5.



a)



b)

Fig. 5 Vertical and horizontal projections. a) From the ROI detectedby match and b) From the ROI detected by rectangles.

b) Normalizing the size of a character

At the final stage we are prepared to detect all the characters inside the plate. We need to apply a normalizationprocess in order to obtain all the characters with the same size. We apply an operation to scale the characters inside the image; this is made by zoom in and zoom out the image. To do this an operation of down sampling and up sampling is executed. In the figure 6 we shown an example of this operation.

Fig .6 the characters zoom in and zoom out by down sampling and up sampling

C.PLATE RECOGNITION

Once we have the coordinates of the characters contained inside the plate, we design a fuzzy neural network.

a) Description of the fuzzy neural network

The great difference between a connectionist machine and typical computer programs is that the first one processes the input information to obtain an output.The perceptron and the adaptive linear neuron (Adeline) net. We have a single layer structure containing a set of input cells and one or more output cells, according to the nature of the problem treated. The structure of a perceptron is shown in figure 7.

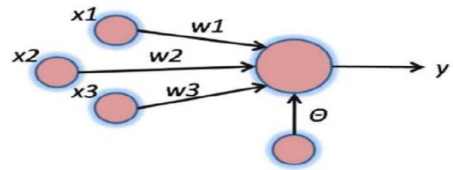


Fig .7 the structure of a classic perceptron.

In order to compute the output *Y* of the perceptron neural network we use the equation 4.

$$y = \sum_{i=1}^{n} w_i x_i \qquad \text{................ (4)}$$

Then, the first layer of the network created is a perceptron, here we have a set of matrices where the initial weights are contained. The second layer, of the network created is again a perceptron, and then we have a multilayer network. In this layer the values are evaluated with a second stage of synapticweights, as a result we obtain the closest value of the threshold. The final layer is added in order to have a betterdiscrimination mechanism. For this, we use the Adeline neural network to minimize the error using the real value produced by the difference of the output layer for a particular input pattern as it is shown in equation 5.

$$\tilde{y} = \sum_{i=1}^{n} w_i x_i + \phi \qquad \text{.........(5)}$$

Each layer of the neural network designed is described as a sum which multiply the input by a synaptic weight for the stages of perceptron, and the difference of the values for the case of the Adeline layer as it is shown in equation 6.

$$y' = \sum_{i=1}^{n} w_i x_i \; AND \; \sum_{j=1}^{m} w_j x_j \; AND \; \sum_{k=1}^{s} w_k x_k + \phi \qquad \text{............ (6)}$$

At the final of the last layer we obtain a fuzzy set which inference rules tries to minimize the error percentage and to offer the better result using the values obtained by the neural network.

b) Methodology to fill the matrices of synaptic weights

The methodology to fill the matrices is different from the classical methodology, where the weights must be random and small. We find the thresholds using the inputs and the matrix can pass the threshold without the training stage. The input patterns are passed to the learning stage in order to compute the activation thresholds. The patterns are passed to each matrix by multiply the weights or by computing the minimum error for the case of Adeline layer.

First layer. To fill the first layer we use the input images which are called the group matrices. The matrix of synaptic weights is filled with the values of five characters using the OR logic function as it is shown in equation 7

$$I_{wI} \sum_{i=1}^{n} I_{x1}\ OR\ I_{x2}\ OR\ I_{x3}\ OR\ I_{x4}\ OR\ I_{x5} \qquad \text{......................} (7)$$

Where $I_{wI}$is the group matrix containing the sum of each $I_{xn}$and each $I_{xn}$is the input image as it is shown in figure 15. We compute the values for each different activation threshold. After the creation of I_{wI}we pass each $I_{xn}$to compute each single threshold. We use a different threshold for each result obtained.

Second layer. To fill the matrix of the second layer we multiply it by a matrix defined for each character pertaining to the group matrix. We need to determine that each result is the closest to each threshold computed.Each threshold is loaded in the time when the group matrix is created, here is necessary to consider the declaration of several inference rules to ensure that result obtained is the closest, even when a character can be similar to other characters pertaining to another group.

Third layer. At the third layer the trained pattern is called again, and the differences inside the Adeline network are computed. If at the final of the second layer the input image has an activation value defining its similarity to the letter "B", we call again the matrix of features for the "B" character. We analyze it using the fuzzy set to determine if the classification obtained is correct, this is valid even when we have two similar values.

c) Fuzzy sets

A set is defined as a collection of well-defined elements. Always it is possible to determine when an element of the set is part or not of the particular set. The main decision is obviously to determine if the element is part of the set or not. We use the methodology of inference fuzzy sets, whose structure is composed by several blocks as is shown in figure 8. Each value to be evaluated represents the grade of difference obtained by the third layer of the fuzzy neural network described.

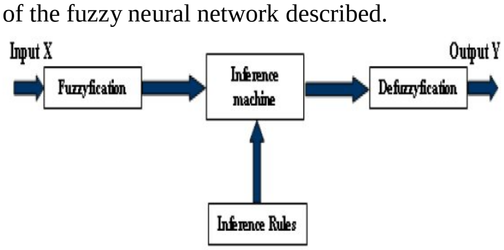


Fig .8 diagram of the inference system.

The fuzzy block allow us to transform each normal value into a fuzzy value, the block of rules contain a set of linguistic rules used to synthesize the knowledge of an expert to solve the problem tackled. The inference machine determines the grade of the value of each rule, at the final the output is transformed by the defuzzy block. The inference rules inside the methodology proposed are created to insure that the character selected is really the most similar.

IV. TEST AND RESULTS

The test images were taken on an uncontrolled environment at the parking lot of our University (Ciudad Juarez). We have three different kinds of plates: local plates of Ciudad Juarez defined by the gray colour strip on the lower part, the plates of the border vehicles defined by a yellow strip on the lower part, and the plates of Texas (El Paso), characterized by larger characters. As we mentioned before, the environment of the imageacquisition was not controlled. In table 1 we presented some results for the case of plate detection. Because the size of the characters is different. After plate detection, we carried out a test for characterrecognition; a key process of this stage is the process of adaptive thresholding.

We detect some cases of positive false that are those results whose detection of a vehicular plate where not correct even when the feature that we find are correct. The features are the size of a plate and that the rectangle detected must be similar at least for a percentage of 40% to be considered as a license plate. This mistake occurs when we use gray scale images where the values are smaller than those of the RGB images. The stage of image thresholding is the key to obtain valid characters.

VI. CONCLUSIONS AND FURTHER WORKS

In this paper we presented a novel methodology to solve the problem of car license plate recognition. The stage of plate detection is solved using two methods: rectangle detection and model pattern comparison. The stage of character detection is solved using an adaptive thresholding method and horizontal and vertical projections. The characters detected are resized in order to obtain always the same size of a character. Finally the problem of recognition was solved using a fuzzy three layer neural network. The results obtained show that the system performs well even when the images were taken on uncontrolled environment and using three different kinds of plates. In the future we are going to design an ideal character database to avoid the problem of character similarity.

Number of images	Plate detected	Failure	Acceptance percentage
25	20	Plate size Light	80%
Number of Characters	Non classified characters	Failure	Acceptance percentage
180	23	Light	87.22 %

Table I overall results obtained.

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