Automatic Number Plate Recognition Using Artificial Neural Network

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Abstract - *Automatic Number Plate Recognition (ANPR) became a very important tool in our daily life because of the unlimited increase of cars and transportation systems, which make it impossible to be fully managed and monitored by humans. Examples are so many, like traffic monitoring, tracking stolen cars, managing parking toll, red-light violation enforcement, border and customs checkpoints.* **Yet, it's a very challenging problem, due to the diversity of plate formats, different scales, rotations and non-uniform illumination conditions during image acquisition.**
The objective of this paper is to provide a novel algorithm for license plate recognition in complex scenes, particularly for the all-day traffic surveillance environment. This is achieved using mathematical morphology and artificial neural network (ANN). A pre-processing step is applied to improve the performance of license plate localization and character segmentation in case of severe imaging conditions. The first and second stages utilize edge detection and mathematical morphology followed by connected component analysis. ANN is employed in the last stage to construct a classifier to categorize the input numbers of the license plate. The algorithm has been applied on 102 car images with different backgrounds, license plate angles, distances, lightening conditions, and colors. The average accuracy of the license plate localization is 97.06%, 95.10% for license plate segmentation, and 94.12% for character recognition. The experimental results show the outstanding detection performance of the proposed method comparing with traditional algorithms.

Key Words: ANPR, Edge Detection, Mathematical Morphology, Connected Component Analysis, LP Extraction, Segmentation, Neural Networks

1. INTRODUCTION

Automatic number plate recognition (ANPR), as an important research field used in computer vision, pattern recognition, image processing and artificial intelligence, is one of the most important aspects of the intelligent transportation system of human society in the 21st century. Automatic Number Plate Recognition is comprised of four main sections: image preprocessing, number (license) plate extraction (localization), character segmentation and character recognition. ANPR can be used to store the images captured by the cameras as well as the text from the license plate, with some configurable memory. ANPR technology tends to be region-specific, owing to plate variation from place to place. The objective of the research is to successfully locate vehicle number plate, segment characters and recognize them given a car image. The system must deal with different angles, distances, scales, resolutions and illumination conditions.

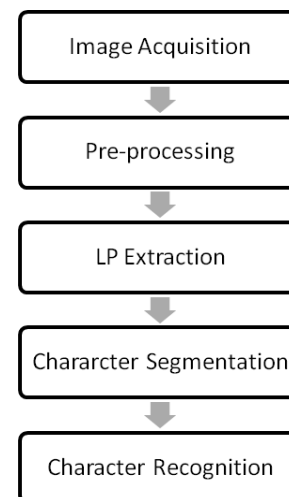## 1.1 Working of Typical ANPR System

Fig -1: Stages of an ANPR System

The ANPR system that extracts a license plate number from a given image can be composed of four stages. The first stage is to acquire the car image using a camera. The parameters of the camera, such as the type of camera, camera resolution, shutter speed, orientation, and light, have to be considered. The second stage is to extract the license plate from the image based on some features, such as the boundary, the color, or the existence of the characters. The third stage is to segment the license plate and extract the characters by projecting their color information, labeling them, or matching their positions with templates. The final stage is to recognize the extracted characters by template matching or using classifiers, such as neural networks, SVMs and fuzzy classifiers. Figure 1 shows the structure of the ANPR process. The performance of an ANPR system relies on the robustness of each individual stage.

2. LITERATURE REVIEW

Recognition algorithms reported in previous research are generally composed of several processing steps, such as extraction of a license plate region, segmentation of characters from the plate, and recognition of each character. Papers that follow this three-step framework arc covered according to their major contribution in this section.

2.1 License Plate Extraction/Localization

Since the license plate normally has a rectangular shape with a known aspect ratio, it can be extracted by finding all possible rectangles in the image. Edge detection methods are commonly used to find these rectangles [1] [2]. In [3], Sobel filter is used to detect edges. Candidate regions are generated in [3], by matching between vertical edges only. In [3], the vertical edges are matched to obtain some candidate rectangles. Rectangles that have the same aspect ratio as the license plate are considered as candidates. This method yielded a result of 96.2% on images under various illumination conditions.

A boundary line-based method combining the HT and contour algorithm achieved extraction results of 98.8% by detecting vertical edges and forming a boundary. Connected component analysis (CCA) is an important technique in binary image processing [4]. 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. A contour detection algorithm is applied on the binary image to detect connected objects. The connected objects that have the same geometrical features as the plate are chosen to be candidates. In [5], color images are segmented by the mean shift algorithm into candidate regions and subsequently classified as a plate or not. The detection rate of 97.6% was obtained.

License plate extraction methods based on locating its characters examine the image for the presence of characters. If the characters are found, their region is extracted as the license plate region. 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. If a linear combination of character-like regions is found, the presence of a whole license plate is assumed. Binary objects that have the same aspect ratio as characters and more than 30 pixels are labeled.

2.2 Character Segmentation

In [6], the bilinear transformation is used to map the tilted extracted license plate to a straight rectangle. A least-squares method is also used to treat horizontal tilt and vertical tilt in license plate images.

Segmentation is performed in [7], [8] by labeling the connected pixels in the binary license plate image. The labeled pixels are analyzed 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. Since characters and license plate backgrounds have different colors, they have opposite binary values in the binary image. Therefore, some proposed methods as in [4], [9], [11], and [13] project 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 [11], 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 10–20ms processing speed. Prior knowledge of characters can help the segmentation of the license plate. In [10], the binary image is scanned by a horizontal line to find the starting and ending positions of the characters. When the ratio between characters pixels to background pixels in this line exceeds a certain threshold after being lower than this threshold, this is considered as the starting position of the characters. The opposite is done to find the ending position of the characters.

2.3 Character Recognition

Template matching is simple and straightforward method in recognition [3], [13]. 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. Template matching is performed in [3] and [12] after resizing the extracted character into the same size. Some of them are Mahalanobis distance and the Bayes decision technique, Jaccard value, Hausdorff distance, and the Hamming distance. Character recognition in [12] uses normalized cross correlation to match the extracted characters with the templates. If a character is different from the template due to any font change, rotation, or noise, the template matching produces incorrect recognition.

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 [13]. The extracted features form a feature vector which is compared with the pre-stored feature vectors to measure the similarity.

In [13], the feature vector is generated by projecting the binary character horizontally and vertically. In [8], 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. In [14], the feature vector is generated by sampling the character contour all around. The resulted waveform is quantized into the feature vector. This method recognizes multi-font and multisize-characters since the contour of the character is not affected by any font or size change. After feature

extraction, many classifiers can be used to recognize characters, such as ANN [8], SVM [9], HMM.

3. PROPOSED ANPR SYSYEM

ANPR has four parts: (i) Pre-processing, (ii) Localization (extraction) of license plate from image, (iii) Segmentation (extraction) of characters from localized license plate region, and (iv) Recognition of those characters. Following figure 2 gives the architecture of proposed ANPR system.

3.1 Pre-processing

Pre-processing of an input image includes various processes like converting an image from RGB to grayscale image, removing noise from the image, binarization, enhancing an image etc. Images are often corrupted by random variations in intensity values, called noise. Some common types of noise are salt and pepper noise, impulse noise and Gaussian noise. Salt and pepper noise contains random occurrences of both black and white intensity values. Median filtering process is a kind of image processing method used to eliminate and minimize unwanted noise and spots of the image.
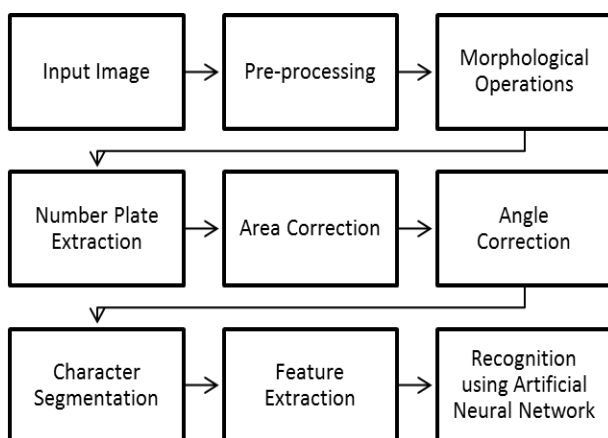

Fig -2: Proposed ANPR System

A global threshold (level) that can be used to convert an **intensity image to a binary image is calculated using Otsu's** Thresholding method, which chooses the threshold to minimize the intraclass variance of the black and white pixels. Threshold (level) is a normalized intensity value that lies in the range [0, 1]. Also a specific mask is applied on the binarized image depending on the approximate position of the number plates in the image database set. This will increase the processing speed by neglecting unnecessary data in the car image directly, thus reducing computational time required at further complex stages.

3.2 LP Extraction/Localization

The purpose of this part is to extract the License Plate from a captured image. The output of this module is the RGB picture of the LP precisely cropped from the captured image, and a binary image which contains the normalized

LP. It consists of edge detection and various morphological operations followed by connected component analysis.

A sobel operator with suitable mask is applied on the image to detect the possible edges. Then different morphological operations are applied to the image. Morphological operations apply a structuring element to an input image, creating an output image of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. We applied dilation process to the image with two linear structuring elements of length 3. It is then followed by holes filling process and the difference image is obtained for further morphological operations. The ULEA (Unwanted Lines Elimination Algorithm) is applied on to the image using 4 linear SEs of length 25 with an angle of 0°, 90°, 45°, 135° respectively. Thus, the resultant image contains only the prominent locations where the LP can be present. We then perform the connected component analysis to remove small objects and label rest of the objects. Then, we measure a set of properties for the extracted number plate, viz. area, bounding box, major axis length, minor axis length and orientation. The standard number plate falls into the certain range of ratio of major axis length to minor axis length. The minimum and maximum area of the number plate also proves to be important parameter for the extraction of number plate. Also, orientation of the number plate helps us to find out the exact location of the number plate. All the lower and upper threshold values are set depending on the standard number plate via trial and error approach. The extracted number plate is then displayed.

3.3 Angle/Area Correction

The method first separates the number plate image into connected components. Then, it processes the candidate selection algorithm, in which the deepest white regions satisfying the following conditions are selected:

- Area > LP_MIN_AREA
- LP_MIN_RATIO<=height/width<=LP_MAX_RATIO
- Area >= max(areas of the candidates)/3.5

LP_MIN_AREA, LP_MIN_RATIO, LP_MAX_RATIO, 3.5 are parameters which were selected after testing multiple images, and should be refined in future works in order to get even more accurate results. If no candidate were found, the method chooses the region with maximum area to be the LP region; otherwise, it chooses the candidate with maximum area. The method returns a rectangular area with safety spacing from the found area.

The angle correction method also determines the angle of the supplied picture relatively to the horizontal. It uses the Radon transform in order to find lines on the picture, and returns the angle of the most visible one. Thus, any angular rotation in the extracted LP image is rectified.

3.4 Character Segmentation

Character Segmentation from the extracted number plate can be divided into two stages, Pre-processing and character segmentation using connected component analysis. The extracted number plate is pre-processed first, so as to perform segmentation perfectly. The preprocessing includes quantization, normalization, labeling connected components and removing small objects, if any.

The quantization method first adjusts the image intensity values; it calculates the histogram of the image and **determines the adjustment limits "low_in" and "high_in"** then, maps the values in the supplied intensity image to new values such that values between low_in and high_in map to values between 0 and 1, values below low_in map to 0, and those above high_in map to 1. In order to perform the character recognition, we should be able to make the difference between digits and background inside the plate. Equalization and quantization permit to obtain a gray scale image with improved contrast between digits and backgrounds, thus obtaining better performance for the binarization process which moreover use adaptive threshold.

Normalization transforms the image into a rectangular matrix (by turning and stretching) whose normalized size is 50x150. The method also transforms the binary image into its complement. It also determines the LP horizontal contours and removes vertical small noise from the picture. CCA is performed once again for segmenting each character. All the labeled connected components are evaluated on the basis of their area and bounding box is applied to them. Each component represents the individual character segmented out of the extracted number plate image. These segmented characters are then resized into a size of [24 12] pixels and displayed.

3.5 GLCM Feature Extraction

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 distinguish characters under any distortion. The extracted features form a feature vector which is compared with the pre-stored feature vectors to measure the similarity.

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. The offset is provided such that two GLCMs are formed

and various properties/features are calculated. The various GLCM features are as follows:

a. Contrast: Returns a measure of the intensity contrast between a pixel and its neighbor over the whole image.
b. Correlation: Returns a measure of how correlated a pixel is to its neighbor over the whole image.
c. Energy: Returns the sum of squared elements in the GLCM.
d. Homogeneity: Returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

The maximum value from the respective set of values is retained. The values are quantized and their mean is calculated and stored as feature vector. This feature is given as input to the feed forward back propagation neural network while training and testing.

3.6 Character Recognition

The feed forward back propagation artificial neural network is created with the set of inputs, outputs and sizes of hidden layers. Also transfer function of each layer and training function of ANN is defined. The default weights and biases are initialized. After this, the network is trained with the training data set which includes feature value as input and desired output. Once the system is perfectly trained, it is tested for the test data set and accuracy is calculated.

The feed forward back propagation neural network is trained for our ANPR system. The system is tested for 102 sample images in our database. For this, it will first calculate the feature vector as described in the previous chapter. This feature vector value will be given to artificial neural network for testing. The artificial neural network will decide upon the feature vector input and recognize characters from the number plate successfully.

4. EXPERIMENTAL RESULTS

For this project, image database of 102 car images is collected manually, which uses a 20.7 megapixel digital camera at a distance of 3-5 meters. Few sample images are given below in figure 3.
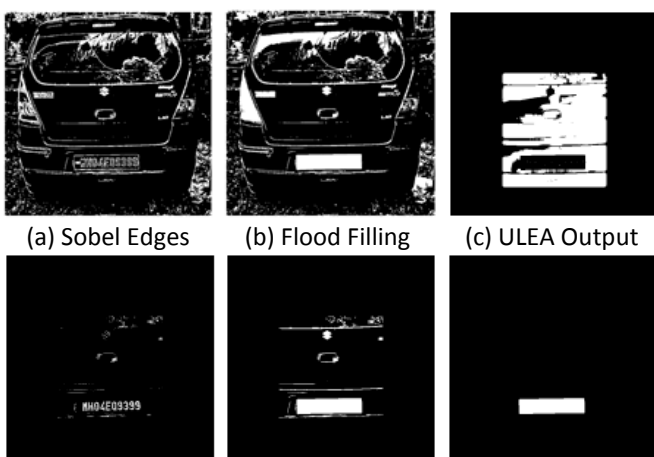
Fig -3: Sample Input Images

Figure 4 shows various pre-processing stages for a sample image shown above.

(a) Gray scale   (b) Median Filtering (c) Binarized Mask
Fig -4: Pre-processing Stages

(a) Sobel Edges   (b) Flood Filling   (c) ULEA Output

(d) Extractred LP   (e) Before CCA   (f) After CCA
Fig -5: Morphological Operations in LP Extraction Process

Figure 5 shows results of various morphological operations and CCA involved in the LP extraction process. In figure 6, we can see the bounding box applied to the LP which is extracted as correct LP region. Figure 7 shows the experimental result of angle correction using Radon transform applied to the extracted LP.


Fig -6: Extracted LP Region

(a) Before Angle Correction   (b) After Angle Correction
Fig -7: Angle Correction using Radon transform

After successfully extracting the LP from the input image, the next process is character segmentation process which is shown in figure 8. After that, the GLCM features are extracted and feature value is fed as input to the artificial neural network for character recognition. Output of character recognition process is displayed in figure 9.
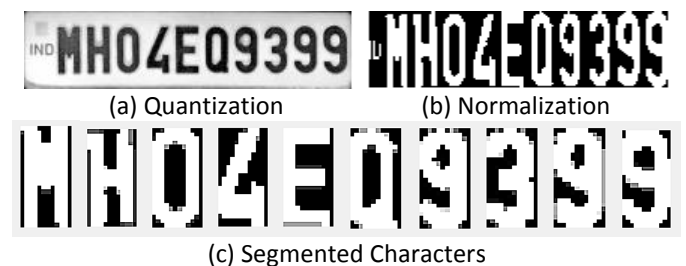
(a) Quantization   (b) Normalization

(c) Segmented Characters
Fig -8: Character Segmentation Process

Fig -9: Charcter Recognition

In this section, the accuracy of individual stage in the automatic number plate recognition process is evaluated and shown in Table 1 given below. The computation time for the proposed ANPR system is calculated and found to

be 400ms for most of the database images, which is fairly acceptable for the real time application of the ANPR system.

Table -1: Accuracy for proposed ANPR System

ANPR Stages	Plate Extraction	Character Segmentation	Character Recognition
Total Images=102	99/102	97/102	96/102
Accuracy	97.06 %	95.1 %	94.12 %

In Table 2, we calculate the training data set accuracy with different levels of errors that have occurred in the optical character recognition process. The experimental results show that the artificial neural network has been trained properly to achieve best results. The recognition accuracy for testing data set is also given in the table given below. The overall accuracy of the recognition using ANN is 94.12% which is better than other recognition techniques discussed in the literature.

Table -2: Recognition Accuracy of ANPR System

Total Images	Correct Recognition	1 Character in Error	2 Characters in Error	> 2 Characters in Error
102	96	4	1	1
Percentage	96/102= 94.12%	4/102= 3.92%	1/102= 0.98%	1/32= 0.98%
Training = 70	67	2	1	0
Percentage	67/70= 95.71%	2/70= 2.86%	1/70= 1.43%	0
Testing = 32	29	1	1	1
Percentage	29/32= 90.63%	1/32= 3.13%	1/32= 3.13%	1/32= 3.13%

5. CONCLUSIONS

Automatic Number Plate Recognition is a rapidly evolving area of research and development in the field of Intelligent Transportation System. Different researchers have provided different methods and techniques for this system. However, every technique has its own advantages and disadvantages.

This paper presented a detailed explanation of the proposed ANPR system by categorizing it according to the features used in each stage. We have used morphological operations for extracting the LP from the image. We have successfully extracted the number plate from most of the images and performed segmentation. The feed forward back propagation neural network gives an excellent recognition rate of 94.12% along with acceptable processing time (400ms) which makes it suitable for real time applications.

FUTURE SCOPE

Although significant progress of ANPR techniques has been made in the last few decades, there is still a lot of work to be done since a robust system should work effectively under a variety of environmental conditions and plate conditions. An effective ANPR system should have the ability to deal with multistyle plates, e.g., different national plates with different fonts and different syntax. License plate recognition can also be used for vehicle manufacturer and model recognition.

There are many other open issues for the future research.

- Video based ANPR systems
- Multi-plates ANPR systems
- Car manufacturer and model recognition

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