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Automatic Number Plate Recognition System

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Abstract: ***The traffic on the roads is increasing day by day. There is dire need of developing an automation system that can effectively manage and control the traffic on roads. The traffic data of multiple vehicle types on roads is important for taking various decisions related to traffic. A video based traffic data collection system for multiple vehicle types is helpful for monitoring vehicles under homogenous and heterogeneous traffic conditions. License plate recognition (LPR) algorithms in images or videos are generally composed of processing steps such as extraction of a license plate region, segmentation of the plate characters and recognition of each character. This task is quite challenging due to the diversity of plate formats and the nonuniform outdoor illumination conditions during image acquisition. Therefore, most approaches work only under restricted conditions such as fixed illumination, limited vehicle speed, designated routes, and stationary backgrounds. Numerous techniques have been developed for LPR in still images or video sequences, and the purpose of this paper is to categorize and assess them. Issues such as processing time, computational power, and recognition rate are also addressed.***

Keywords: License plate detection, Neural network, Recognition, Segmentation, Template matching

1. Introduction

A traffic surveillance camera system is an important part of an intelligent transportation system. It mainly includes automatic monitoring of digital cameras to take snapshots of passing vehicles and other moving objects. The recorded images are high resolution static images, which can provide valuable clues for police and other security departments, such as a vehicle plate number, the time it passed, its movement path and the drivers face, etc. In prior days, massive amounts of stored images were processed manually, but this required hard work and resulted in poor efficiency. With the rapid development of computer technology, automatic license plate recognition software is utilized at an increasing rate in the field with great success. Unfortunately, sometimes we may not discover the license plate of a vehicle because of cloned license plates, missing license plates, or because the license plate cant be recognized. This is why automatic vehicle detection and recognition is becoming the imminent requirement for traffic surveillance applications. This technology will save a lot of time and effort for users trying to identify blacklisted vehicles or who are searching for specific vehicles from a large surveillance image database. On analysing the literature in the domain we have identified 3 subsections and for each subsection so many algorithms are there.

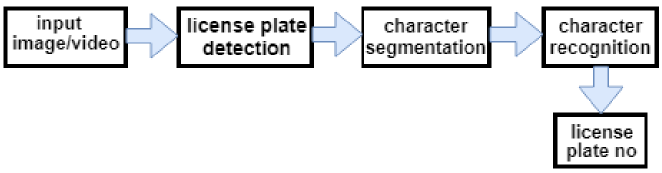

Figure 1: Architecture of ANPR system

Architecture of the license plate detection is shown in figure1. It consist of 3 main sections
1. License plate detection
2. Character segmentation
3. Character recognition

2. Scope of this Survey

Papers that follow the three-step framework are surveyed and classified according to their major methodology. From this several issues such as performance, execution time, and recognition rate for each method are reported.it is inappropriate to explicitly declare which methods actually demonstrate the highest performance. One of the scope of this survey is to find best method in real life for finding the license plate. For this, characteristics such as type and colour of plates, illumination conditions, various angles of vision, are considered from several survey papers.

3. Literature Survey

Literature review is divided into 3 sections: License plate detection, segmentation and character recognition

3.1 License plate detection

License plate location is an integral and inseparable part of the system, as it locates the plate that encloses the license plate numbers. The whole concept depends on the edges of the license plate since there are huge data in the image. The extraction of multiple license plates from an image with a complex background is the main factor. Different processes are performed to extract the license plate. The extractor gives its output to the segmentation part.

3.1.1 Edge statistics and morphological process

Techniques based upon combinations of edge statistics and mathematical morphology [1], [2] featured very good results. In these methods, gradient magnitude and their local variance in an image are computed. They are based on the property that the brightness change in the license plate region is more remarkable and more frequent than otherwise. Edge based methods alone can hardly be applied to complex images, since they are too sensitive to unwanted edges, which may also show a high edge magnitude or variance .To overcome this situation we used the combination of edge statistics and morphological process. When combined with morphological steps that eliminate unwanted edges in the processed images, the license plate extraction rate is relatively high and fast compared to other methods. Mathematical morphology consists of 2 algorithms, erosion and dilation process. Erosion is a morphological process that can be obtained by dilating the compliment of the black pixels and taking the compliment of the resulting point set. The average accuracy of locating a vehicle LP is an impressive rate of 99.6

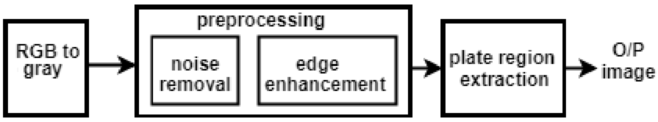

Figure 2: License plate detection using morphological process

3.1.2 Connected component analysis

Connected component analysis (CCA) is a vital technique in binary image processing that scans an already binarized image and labels its pixels into components based on pixel connectivity (either 4-connected or, usually, 8- connected). Once all groups of pixels have been determined, each pixel is labelled with a value according to the component to which it was assigned. Extracting and labelling of various disjoint and connected components in an image is basic to many automated image analysis applications, as many helpful measurements and features in binary objects may be extracted. Spatial measurements such as area, orientation, and aspect ratio (AR) are just few of the features frequently integrated in image processing algorithms for LP detection [3], [4]. Then, using simple filtering techniques, binary objects with measurements that exceed the desired limits can be eliminated in the next algorithmic steps [5]. Text detection from complex background image is also possible in this method. Text regions have been successfully extracted irrespective of the text font and size.

3.1.3 Color based processing

Color or gray-scale-based processing methods are proposed in the literature for license plate location [6] [7]. Crucial to the success of the color (or gray level)-based method is the color (gray level) segmentation stage. On the other hand, solutions currently available do not provide a high degree of accuracy in a natural scene as color is not stable when the lighting conditions change. Since these methods are generally color based, they fail at detecting various license plates with varying colors.Though color processing shows better performance, it still has difficulties recognizing a car image if the image has many similar parts of color values to a plate region. An enhanced color texture based method for detecting license plates (LPs) in images was presented in [8]. The system analyses the color and textural properties of LPs in images using a support vector machine (SVM) and locates their bounding boxes by applying a continuous adaptive mean shift (CAMShift) algorithm. The combination of CAMShift and SVMs produced efficient LP detection as time-consuming color texture analysis for less relevant pixels were restricted, leaving only a small part of the input image to be analysed. Yet, the proposed method still encountered problems when the image was extremely blurred or quite complex in color. An example of time-consuming texture analysis is presented in [9], where a combination of a kdtree data structure and an approximate nearest neighbour was adopted. The computational resource demand of this segmentation technique was the main drawback, since it yielded an execution time unacceptable for LPR (34 s)

3.1.4 Gabor filter

Gabor filters have been one of the major tools for texture analysis. This technique has the advantage of analysing texture in an unlimited number of directions and scales. A method for license plate location based on the Gabor transform is presented in [10]. The results were encouraging (98 % for LP detection) when applied to digital images acquired strictly in a fixed and specific angle, but the method is computationally expensive and slow for images with large analysis. For a two-dimensional (2-D) input image of size N×N and a 2-D Gabor filter of size W×W the computational complexity of 2D Gabor filtering is in the order of W^2N^2 given that the image orientation is fixed at a specific angle. Therefore, this method was tested on small sample images and it was reported that further work remain to be done in order to alleviate the limitations of 2-D Gabor filtering.

3.1.5 Hough transform

In the method that uses Hough transform (HT), edges in the input image are detected first. Then, HT is applied to detect the LP regions. In [11], the authors acknowledge that the execution time of the HT requires too much computation when applied to a binary image with great number of pixels. As a result, the algorithm they used was a combination of the HT and a contour algorithm, which produced higher accuracy and faster speed so that it could be applied to real-time systems. However, since HT is very sensitive to boundary deformation, this approach achieved very good results (98.8% average accuracy) when applied only to close shots of the vehicle.

3.1.6 Wavelet based transform

A wavelet transform-based method is used in [12] for the extraction of important contrast features used as guides to search for desired license plates. Applying wavelet transform to an image and projecting the acquired detail information, a wave crest that indicates position of a license plate will be generated. [13] propose a multiwavelet with EMD analysis for identifying the license plate. It is useful for detecting license plate under various conditions from various countries. The major advantage of wavelet transform, when applied for license plate location, is the fact that it can locate multiple plates with different orientations in one image and detect blurry images. Nevertheless, the method is unreliable when the distance between the vehicle and the acquisition camera is either too far or too close.EMD analysis will mistakenly detect the wave crest that indicate the region containing the similar contrast feature instead of the true wave crest.

3.2 Character Segmentation

License plate segmentation process is also called as the Character Separation. After the license plate images are extracted from a picture, find individual character in the license plate to recognize it. In the segmentation of license plate characters, license plate is first converted into a binary image and then characters are divided into segments. License plate Segmentation is useful to outline the individual characters. License plate segmentation, which is referred to as character isolation takes the region of interest and attempts to split it into individual characters

3.2.1 Projections and Binary Algorithms

Reviewing the literature, it was evident that the method that exploits vertical and horizontal projections of the pixels [14], [6], [15], [16] is the most common and simplest one. Obtaining a binary image, the idea is to add up image columns or rows and obtain a vector (or projection), whose minimum values allow us to segment characters (see Figure.3).CCA is also intensely involved in character segmentation, in conjunction with binary object measurements such as height, width, area [1], and orientation [17] [18]. In other cases, CCA is supported by either VQ or mathematical morphology. Usually, the CCA method labels the pixels into components based on 8-neighborhood connectivity, but the binarized image is decomposed into 4-neighbor connected components

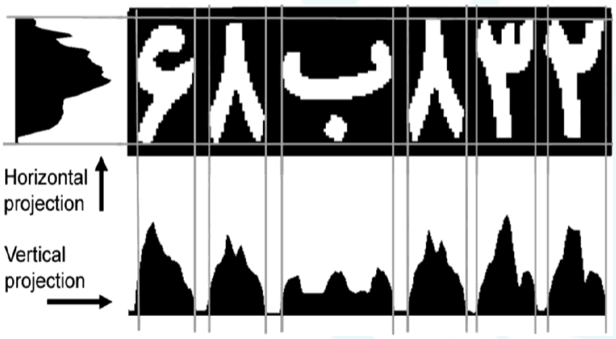

Figure 3: Character extraction using the horizontal and vertical projection method

3.2.2 Contours

Contour tracking and modelling is also incorporated for character segmentation. In [19], an algorithm inspired by the contour tracking method known as bug following [20] is implemented for character segmentation. Capar and Gokmen established a shape-driven active contour model, which utilizes a variational fast marching algorithm, and applied it to the plate character-segmentation problem. First, coarse location of each character is found by an ordinary fast marching technique [21] combined with a gradient- and curvature dependent speed function, as presented in [22]. The method proceeds with the segmentation of exact boundaries through the calculation of a special fast marching methodology, which depends on gradient, curvature, and shape similarity information. Shape similarity statistics were again embedded into a fast marching method to stop the evolving front when the front resembles one of the trained shapes (e.g., top of Figure. 4). In addition, Figure. 4 (bottom) demonstrates an example of initially broken characters and the final merged segmentation results using this method

Figure 4: (Top) Segmentation sequence. (Bottom) Merging broken characters

3.2.3 Histogram and morphological process

The work in [15] proposed a novel adaptive approach for character segmentation and feature vector extraction from seriously degraded images. An algorithm based on the histogram automatically detects fragments and merges these fragments before segmenting the fragmented characters. A morphological thickening algorithm automatically locates reference lines for separating the overlapped characters. A morphological thinning algorithm and the segmentation cost Calculation automatically determine the baseline for segmenting the connected characters. Basically, this approach can detect fragmented, overlapping, or connected characters and adaptively apply one of three algorithms without manual fine tuning. The results are very promising and encouraging, indicating that the method could be used for character segmentation in plates with not easily distinguishable characters during off-line operation, but since the algorithm is computationally complex,it cannot be proposed for real-time LPR.

3.2.4 Classifier

The method proposed in [23] is different from many existing single-frame approaches, because it simultaneously utilizes spatial and temporal information. First, it models the extraction of characters as a Markov random field (MRF), where the randomness is used to describe the uncertainty in pixel label assignment. MRF models can be used to incorporate prior contextual information or constraints in a quantitative way. Local spatial/contextual dependences can be utilized to perform binarization. Therefore, Cui and Huang prove that by using the MRF modelling, the extraction of characters can be modelled as the problem of maximizing a posteriori probability based on given prior knowledge and observations. After that, a GA with a local greedy mutation operator is employed to optimize the objective function and speed up the convergence based on [24]. The method was developed for LP character segmentation in video sequences.

3.3. Character Recognition

License Plate Recognition is the last step of the LPR system. This step is the main part of the recognition process which decides the accuracy and recognition rate of the system. This Recognition involves about to recognize the characters of the license plate numbers and character. Before the recognition the license plate characters are normalized. Normalization is to improve the characters into a block containing no added white spaces (pixels) in all the four sides of the characters. In this Stage, the license plate character images that are taken out from the license plate image have to be recognized. It is actually the process of the character recognition of the license plate characters. The character recognition of the license plate can be find out through Neural Network, Template matching, Hough Transform, Radial Basic Function.

3.3.1 Classifiers

Statistical/Hybrid Classifiers

When hidden Markov models (HMMs) are employed, the recognition begins with pre-processing and parameterization of the ROIs detected in the previous phase (character segmentation). Based on [28], the recognition result in [15] was reported to be 95.7complex procedure of preprocessing and parameterization for the HMMs: one for every character. The authors also reported that the width of the plate in the image after rescaling lies between 25and 600 pixels). This reveals the necessity for good character analysis when implementing HMMs, which poses a restriction on the effective distance of the plate recognition system. This prerequisite is also featured in [25], where the recognition results reached 92.5 Furthermore, the authors in [27] designed a system that implements SVMs and reports an impressive average character recognition rate of 97.2character recognizers were applied to recognize upper characters, upper numerals, lower characters, and lower numerals on the plate

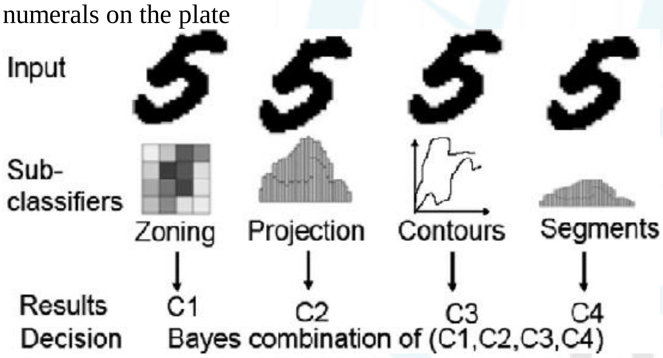

Figure 5: Statistical classification stage combining four sub-classifiers using the Bayes method

Many researchers integrate two kinds of classification schemes [21], [18], multistage classification schemes [26], or a parallel combination of multiple classifiers [23][8]. Pan et al.[25] proposed a two-stage hybrid recognition system that combines statistical and structural recognition methods to achieve robust and high recognition performance. Initially, skew images of car plates were corrected and normalized. In the first recognition stage, four statistical subclassifiers (SC1, SC2, SC3, and SC4) independently recognize the input character, and the recognition results are combined using the Bayes method [83]. Subclassifier SC1 uses the zoning density. SC2 uses the vertical projections, SC3 calculates the contour profile, and SC4 counts line segments in each row and column (see Fig. 5). Finally, if the output of the first (statistical) stage contains characters that belong to prescribed sets of similar characters, the second (structural) stage is initiated as a complement to the first. Structure features are obtained and are then fed into a decision tree classifier. The success ratio reached 95.41,huge testing data set of more than 10 000 plates. Alternatively, coarse-to-fine classification is an efficient way to organize object recognition to accommodate a large number of possible hypotheses and to systematically exploit shared attributes and the hierarchical nature of the visual world. The basic structure is a nested representation of the space of hypotheses and a corresponding hierarchy of (binary) classifiers [32]. A scene is processed by visiting nonoverlapping 5 x 5 blocks, processing the surrounding image data to extract spread edge features based on the research conducted and classifying this sub image according to the coarse to- fine search strategy. There are 37 classes defined by the prototypes (bit maps), shown at the top of Figure 5, which correspond to the 36 alphanumerical characters plus the special character "—". Special emphasis was given to pairwise competition between any two similar interpretations of a character (e.g., S/5 and J/U). The algorithm was evaluated on 520 plates. The correct character string was found on all but 17 plates. However, the classification rate per symbol was much higher: more than 99.

3.3.2 Template matching

The template matching technique is a suitable technique for the recognition of single-font, not-rotated, and fixed-size characters. It is a technique to identify the segmented character by finding the small part in image that match with the template this method need character image as their template to store in the database. Template matching requires a library of a wide variation of character fonts and thicknesses. In order to create the templates for each character do the following operation: For every white pixel we insert the value 1 and for every black pixel 0. We do this for all the 50 training samples for each character and calculate the weights to get the template. Template matching is an effective algorithm for recognition of characters. The character image is compared with the ones in the database and the best similarity is measured. Calculate the matching score of the segmented character from the templates of the character stored algorithm. Compare the pixel values of the matrix of segmented character and the template matrix, and for every match we add 1 to the matching score and for every miss-match we decrements 1. This has done for all pixels. The match score is generated for every template and the one which gives the highest score is taken to be the recognized character. The character template that best matches the input characters are then displayed. Finally, the Hausdorff distance is a method of comparing two binary images (or two sets of active pixels). The method possesses all the mathematical properties of a metric, and its recognition rate is very similar to that obtained with neural network classifiers but slightly slower. On the basis of the research conducted in [25]and [26], Martin et al. concluded that the Hausdorff distance may constitute a complementary recognition method if real-time requirements are not very strict

3.3.3 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) sometimes known as neural network is a mathematical term, which contains interconnected artificial neurons. Several algorithms such as [27], [6], [28], [29], are based on ANN. In [27] two layer probabilistic neural network with the topology of 180-180-36. The character recognition process was performed in 128ms. In [30] multi layered perceptron (MLP) ANN model is used for classification of characters. It contains input layer for decision making, hidden layer to compute more complicated associations and output layer for resulting decision. Feed forward back-propagation (BP) algorithm was used to train ANN. BP neural network based systems are proposed in [29], with the processing time of 0.06s. In [31] HNN is applied to reduce ambiguity between the similar characters e.g. 8 and B, 2 and Z etc. The authors claim to have more than 99% recognition rate.

3.3.4 Kernel method

Kernel methods, including support vector machines (SVMs) [32] primarily and kernel PCA, kernel FDA, etc., are receiving increasing attention and have shown superior performance in pattern recognition. Kernel methods use a kernel function to represent the inner product of two patterns in expanded nonlinear feature space (possibly of infinite dimensionality). Both training and classification are performed via the kernel function without explicit access of the nonlinear space. An SVM is a binary classifier with discriminant function being the weighted combination of kernel functions over all training samples. The weights (coefficients) are learned by quadratic programming (QP) with the aim of maximizing the margin in feature space. After learning, the samples of non-zero weights are called support vectors (SVs), which are stored and used in classification. The maximal margin criterion of SVM learning leads to good generalization performance, but the resulting large number of SVs brings about heavy storage and computation in classification. For multi-class classification, binary SVMs can be combined in two ways: one-versus-all (one-against-others) or one-versus-one (pairwise). The pairwise combination scheme was shown to outperform one-versus-all when using linear kernel.When nonlinear kernels are used, the one-versus-all scheme performs sufficiently. In recent years, many results of character recognition using SVM classification have been reported, mostly for small category set problems like numeral recognition. The results shows that SVMs indeed yield higher accuracies than statistical and neural classifiers, but the storage and computation of large number of SVs are expensive. A strategy to alleviate the computation cost is to use a statistical or neural classifier for selecting two candidate classes, which are then discriminated by SVM [32]. Dong et al. used a one-versus-all scheme for large set Chinese character recognition with fast training. They speed up the recognition by using a coarse classifier for candidate selection, but cannot avoid the problem of storing large number of SVs.

4. Conclusion

Among license plate detection methods, Edge Statistics and Morphological process method gives good result. It gives an impressive rate of 99.6 %. For character segmentation, high segmentation rate is shown by Connected Component Analysis and Markov Random Field methods. Accurate results can be achieved for character recognition through Deep neural network, even though it takes more time. Some of the works uses artificial neural network based methods for performing both segmentation and character recognition. LPR, as a means of vehicle identification, may be further exploited in various ways such as vehicle model identification, under-vehicle surveillance, speed estimation, and intelligent traffic management.

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