

Automatic License Plate Recognition (ALPR): A State-of-the-Art Review

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Abstract—Automatic license plate recognition (ALPR) is the extraction of vehicle license plate information from an image or a sequence of images. The extracted information can be used with or without a database in many applications, such as electronic payment systems (toll payment, parking fee payment), and freeway and arterial monitoring systems for traffic surveillance. The ALPR uses either a color, black and white, or infrared camera to take images. The quality of the acquired images is a major factor in the success of the ALPR. ALPR as a real-life application has to quickly and successfully process license plates under different environmental conditions, such as indoors, outdoors, day or night time. It should also be generalized to process license plates from different nations, provinces, or states. These plates usually contain different colors, are written in different languages, and use different fonts; some plates may have a single color background and others have background images. The license plates can be partially occluded by dirt, lighting, and towing accessories on the car. In this paper, we present a comprehensive review of the state-of-the-art techniques for ALPR. We categorize different ALPR techniques according to the features they used for each stage, and compare them in terms of pros, cons, recognition accuracy, and processing speed. Future forecasts of ALPR are given at the end.

Index Terms—Automatic license plate recognition (ALPR), automatic number plate recognition (ANPR), car plate recognition (CPR), optical character recognition (OCR) for cars.

I. INTRODUCTION

AUTOMATIC license plate recognition (ALPR) plays an important role in numerous real-life applications, such as automatic toll collection, traffic law enforcement, parking lot access control, and road traffic monitoring [1]–[4]. ALPR recognizes a vehicle's license plate number from an image or images taken by either a color, black and white, or infrared camera. It is fulfilled by the combination of a

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Fig. 1. (a) Standard Alberta license plate. (b) Vanity Alberta license plate.

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. The variations of the plate types or environments cause challenges in the detection and recognition of license plates. They are summarized as follows.

1) Plate variations:

- a) *location*: plates exist in different locations of an image;
- b) *quantity*: an image may contain no or many plates;
- c) *size*: plates may have different sizes due to the camera distance and the zoom factor;
- d) *color*: plates may have various characters and background colors due to different plate types or capturing devices;
- e) *font*: plates of different nations may be written in different fonts and language;
- f) *standard versus vanity*: for example, the standard license plate in Alberta, Canada, has three and recently (in 2010) four letters to the left and three numbers to the right, as shown in Fig. 1(a). Vanity (or customized) license plates may have any number of characters without any regulations, as shown in Fig. 1(b);
- g) *occlusion*: plates may be obscured by dirt;
- h) *inclination*: plates may be tilted;
- i) *other*: in addition to characters, a plate may contain frames and screws.

2) Environment variations:

- a) *illumination*: input images may have different types of illumination, mainly due to environmental lighting and vehicle headlights;
- b) *background*: the image background may contain patterns similar to plates, such as numbers stamped on a vehicle, bumper with vertical patterns, and textured floors.

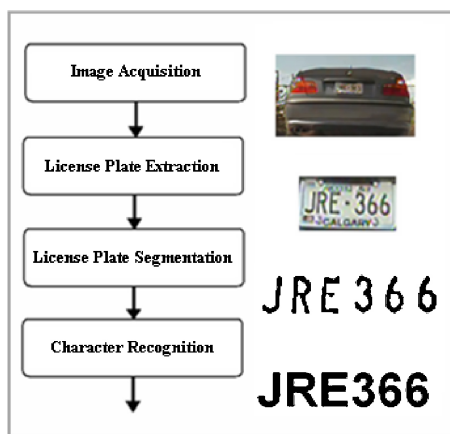


Fig. 2. Four stages of an ALPR system.

The ALPR system that extracts a license plate number from a given image can be composed of four stages [5]. 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 and fuzzy classifiers. Fig. 2 shows the structure of the ALPR process. The performance of an ALPR system relies on the robustness of each individual stage.

The purpose of this paper is to provide researchers with a systematic survey of existing ALPR research by categorizing existing methods according to the features they used, analyzing the pros or cons of these features, and comparing them in terms of recognition performance and processing speed, and to open some issues for the future research.

The remainder of this paper is organized as follows. In Section II, license plate extraction methods are classified with a detailed review. Section III demonstrates character segmentation methods and Section IV discusses character recognition methods. At the beginning of each section, we define the problem and its levels of difficulties, and then classify the existing algorithms with our discussion. In Section V, we summarize this paper and discuss areas for future research.

II. LICENSE PLATE EXTRACTION

The license plate extraction stage influences the accuracy of an ALPR system. The input to this stage is a car image, and the output is a portion of the image containing the potential license plate. The license plate can exist anywhere in the image. Instead of processing every pixel in the image, which increases the processing time, the license plate can be distinguished by its features, and therefore the system processes only the pixels that have these features. The features are derived from the license plate format and the characters constituting it. License

plate color is one of the features since some jurisdictions (i.e., countries, states, or provinces) have certain colors for their license plates. The rectangular shape of the license plate boundary is another feature that is used to extract the license plate. The color change between the characters and the license plate background, known as the texture, is used to extract the license plate region from the image. The existence of the characters can be used as a feature to identify the region of the license plate. Two or more features can be combined to identify the license plate.

In the following, we categorize the existing license plate extraction methods based on the features they used.

A. License Plate Extraction Using Boundary/Edge Information

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 [8]–[11].

In [5], [9], and [12]–[15], Sobel filter is used to detect edges. Due to the color transition between the license plate and the car body, the boundary of the license plate is represented by edges in the image. The edges are two horizontal lines when performing horizontal edge detection, two vertical lines when performing vertical edge detection, and a complete rectangle when performing both at the same time.

In [7], the license plate rectangle is detected by using the geometric attribute for locating lines forming a rectangle.

Candidate regions are generated in [5], [9], [12], and [16] by matching between vertical edges only. The magnitude of the vertical edges on the license plate is considered a robust extraction feature, while using the horizontal edges only can result in errors due to car bumper [10]. In [5], 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. According to [9], if the vertical edges are extracted and the background edges are removed, the plate area can easily be extracted from the edge image. The detection rate in 1165 images was around 100%. The total processing time of one 384×288 image is 47.9 ms.

In [17], a new and fast vertical edge detection algorithm (VEDA) was proposed for license plate extraction. VEDA showed that it is faster than Sobel operator by about seven to nine times.

The block-based method is also presented in the literature. In [18], blocks with high edge magnitudes are identified as possible license plate areas. Since block processing does not depend on the edges of the license plate boundary, it can be applied to an image with an unclear license plate boundary. The accuracy of 180 pairs of images is 92.5%.

In [19], a license plate recognition-based strategy for checking inspection status of motorcycles was proposed. Experiments yielded a recognition rate of 95.7% and 93.9% based on roadside and inspection station test images. It takes 654 ms on a ultramobile personal computer and about 293 ms on a PC to recognize a license plate.

Boundary-based extraction that uses Hough transform (HT) was described in [13]. It detects straight lines in the image to locate the license plate. The Hough transform has the advantage of detecting straight lines with up to 30° inclination [20]. However, the Hough transform is a time and memory consuming process. In [21], a boundary line-based method combining the HT and contour algorithm is presented. It achieved extraction results of 98.8%.

The generalized symmetry transform (GST) is used to extract the license plate in [22]. After getting edges, the image is scanned in the selective directions to detect corners. The GST is then used to detect similarity between these corners and to form license plate regions.

Edge-based methods are simple and fast. However, they require the continuity of the edges [23]. When combined with morphological steps that eliminate unwanted edges, the extraction rate is relatively high. In [8], a hybrid method based on the edge statistics and morphology was proposed. The accuracy of locating 9786 vehicle license plates is 99.6%.

B. License Plate Extraction Using Global Image Information

Connected component analysis (CCA) is an important technique in binary image processing [4], [24]–[26]. 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 [27], [28]. Reference [28] applied CCA on low resolution video. The correct extraction rate and false alarms are 96.62% and 1.77%, respectively, by using more than 4 h of video.

In [29], 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. This algorithm can fail in the case of bad quality images, which results in distorted contours.

In [30], 2-D cross correlation is used to find license plates. 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 is time consuming. It is of the order of n^4 for $n \times n$ pixels [14].

C. License Plate Extraction Using Texture Features

This kind of method depends on the presence of characters in the license plate, which results in significant change in the grey-scale level between characters color and license plate background color. It also results in a high edge density area due to color transition. Different techniques are used in [31]–[39].

In [31] and [39], scan-line techniques are used. The change of the grey-scale level results in a number of peaks in the scan line. This number equals the number of the characters.

In [40], the vector quantization (VQ) is used to locate the text in the image. VQ representation can give some hints about the contents of image regions, as higher contrast and more details are mapped by smaller blocks. The experimental results showed 98% detection rate and processing time of 200 ms using images of different quality.

In [41], the sliding concentric windows (SCW) method was proposed. In this method, license plates are viewed as irregularities in the texture of the image. Therefore, the abrupt changes in the local characteristics are the potential license plate. In [42], a license plate detection method based on sliding concentric windows and histogram was proposed.

Image transformations are also widely used in license plate extraction. Gabor filters are one of the major tools for texture analysis [43]. This technique has the advantage of analyzing texture in unlimited orientations and scales. The result in [44] is 98% when applied to images acquired in a fixed and specific angle. However, this method is time-consuming.

In [32], spatial frequency is identified by using discrete Fourier transform (DFT) because it produces harmonics that are detected in the spectrum analysis. The DFT is used in a row-wise fashion to detect the horizontal position of the plate and in a column-wise fashion to detect the vertical position.

In [36], the wavelet transform (WT)-based method is used for the extraction of license plates. In WT, there are four subbands. The subimage HL describes the vertical edge information and LH describes the horizontal one. The maximum change in horizontal edges is determined by scanning the LH image and is identified by a reference line. Vertical edges are projected horizontally below this line to determine the position based on the maximum projection. In [45], the HL subband is used to search the features of license plate and then to verify the features by checking if in the LH subband there exists a horizontal line around the feature or not. The execution time of license plate localization is less than 0.2 s with an accuracy of 97.33%.

In [46]–[48], adaptive boosting (AdaBoost) is combined with Haar-like features to obtain cascade classifiers for license plate extraction. The Haar-like features are commonly used for object detection. Using the Haar-like features makes the classifier invariant to the brightness, color, size, and position of license plates. In [46], the cascade classifiers use global statistics, known as gradient density, in the first layer and then Haar-like features. Detection rate in this paper reached 93.5%. AdaBoost is also used in [49]. The method presented a detection rate of 99% using images of different formats, size, and under various lighting conditions.

All the methods based on texture have the advantage of detecting the license plate even if its boundary is deformed. However, these methods are computationally complex, especially when there are many edges, as in the case of a complex background or under different illumination conditions.

D. License Plate Extraction Using Color Features

Since some countries have specific colors for their license plates, some reported work involves the extraction of license plates by locating their colors in the image.

The basic idea is that the color combination of a plate and characters is unique, and this combination occurs almost only in a plate region [50]. According to the specific formats of Chinese license plates, Shi *et al.* [50] proposed that all the pixels in the input image are classified using the hue, lightness, and saturation (HLS) color model into 13 categories.

In [51], a neural network is used to classify the color of each pixel after converting the RGB image into HLS. Neural network outputs, green, red, and white are the license plate colors in Korea. The same license plate color is projected vertically and horizontally to determine the highest color density region that is the license plate region.

In [52], since only four colors (white, black, red, and green) are utilized in the license plates, the color edge detector focuses only on three kinds of edges (i.e., black–white, red–white, and green–white edges). In the experiment, 1088 images taken from various scenes and under different conditions are employed. The license plate localization rate is 97.9%

Genetic algorithm (GA) is used in [53] and [54] as a search method for identifying the license plate color. In [54], from training pictures with different lighting conditions, a GA is used to determine the upper and lower thresholds for the plate color. The relation between the average brightness and these thresholds is described through a special function. For any input picture the average brightness is determined first, and then from this function the lower and upper thresholds are obtained. Any pixel with a value between these thresholds is labeled. If the connectivity of the labeled pixels is rectangular with the same aspect ratio of the license plate, the region is considered as the plate region.

In [55], Gaussian weighted histogram intersection is used to detect the license plate by matching its color. To overcome the various illumination conditions that affect the color level, conventional HI is modified by using Gaussian function. The weight that describes the contribution of a set of similar colors is used to match a predefined color.

The collocation of license plate color and characters color is used in [56] to generate an edge image. The image is scanned horizontally and if any pixel that has a value within the license plate color range is found, the color value of its horizontal neighbors is checked. If two or more neighbors are within the same character color range, this pixel is identified as an edge pixel in a new edge image. All edges in the new image are analyzed to find candidate license plate regions.

In [57] and [58], 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. In [59], a fast mean shift method was proposed.

To deal with the problem of illumination variation associated with the color-based method, [60] proposed a fuzzy logic based method. The hue, saturation, and value (HSV) color space is employed. Three components of the HSV are first mapped to fuzzy sets according to different membership functions. The fuzzy classification function is then described by the fusion of three weighted membership degrees.

Reference [61] proposed a new approach for vehicle license plate localization using a color barycenters hexagon model that is lower sensitive to the brightness.

Extracting a license plate using color information has the advantage of detecting inclined and deformed plates. However, it also has several difficulties. Defining the pixel color using the RGB value is very difficult, especially in different illumination conditions. The HLS, which is used as an alternative color model, is very sensitive to noise. Methods that use color

projection suffer from wrong detection, especially when some parts of the image have the same license plate color such as the car body.

In [62], the HSI color model is adopted to select statistical threshold for detecting candidate regions. This method can detect candidate regions when vehicle bodies and license plates have similar color. The mean and standard deviation of hue are used to detect green and yellow license plate pixels. Those of saturation and intensity are used to detect green, yellow, and white license plate pixels from vehicle images.

E. 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 [63], 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 [64] 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 [65], binary objects that have the same aspect ratio as characters and more than 30 pixels are labeled. The Hough transform is applied on the upper side of these labeled 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.

In [66], the characters are extracted using scale-space analysis. The method extracts large-size blob-type figures that consist of smaller line-type figures as character candidates.

In [67], the character region is first recognized by identifying the character width and the difference between the background and the character region. The license plate is then extracted by finding the inter-character distance in the plate region. This method yielded an extraction rate of 99.5%.

In [68], an initial set of possible character regions are obtained by the first stage classifier and then passed to the second stage classifier to reject noncharacter regions. Thirty-six AdaBoost classifiers serve as the first stage classifier. In the second stage, a support vector machine (SVM) trained on scale-invariant feature transform (SIFT) descriptors is employed. In [69], maximally stable extremal regions are used to obtain a set of character regions. Highly unlike regions are removed with a simplistic heuristic-based filter. The remaining regions with sufficient positively classified SIFT keypoints are retained as likely license plate regions.

These methods of extracting characters from the binary image as defining the license plate region are time consum-

TABLE I
PROS AND CONS OF EACH CLASS OF LICENSE PLATE EXTRACTION METHODS

Methods	Rationale	Pros	Cons	References
Using boundary features	The boundary of license plate is rectangular.	Simplest, fast and straightforward.	Hardly be applied to complex images since they are too sensitive to unwanted edges.	[5], [8]–[16]
Using global image features	Find a connected object whose dimension is like a license plate.	Straightforward, independent of the license plate position.	May generate broken objects.	[27]–[30]
Using texture features	Frequent color transition on license plate.	Be able to detect even if the boundary is deformed.	Computationally complex when there are many edges.	[31], [39]–[41]
Using color features	Specific color on license plate.	Be able to detect inclined and deformed license plates.	RGB is limited to illumination condition, HLS is sensitive to noise.	[50]–[52]
Using character features	There must be characters on the license plate.	Robust to rotation.	Time consuming (processing all binary objects), produce detection errors when other text in the image.	[63], [64]
Using two or more features	Combining features is more effective.	More reliable.	Computationally complex.	[70]–[72], [74], [81]

ing because they process all binary objects. Moreover, these methods produce errors when there is other text in the image.

F. License Plate Extraction Combining Two or More Features

In order to effectively detect the license plate, many methods search two or more features of the license plate. The extraction methods in this case are called hybrid extraction methods [47].

Color feature and texture feature are combined in [70]–[74]. In [70], fuzzy rules are used to extract texture feature and yellow colors. The yellow color values, obtained from sample images, are used to train the fuzzy classifier of the color feature. The fuzzy classifier of the texture is trained based on the color 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. In [71], two neural networks are used to detect texture feature and color feature. One is trained for color detection and the other is trained for texture detection using the number of edges inside the plate area. The outputs of both neural networks are combined to find candidate regions. In [72], only one neural network is used to scan the image by using $H \times W$ window, similar to the license plate size, and to detect color and edges inside this window to decide if it is a candidate. In [73], the neural network is used to scan the HLS image horizontally using a $1 \times M$ window where M is approximately the license plate width, and vertically using an $N \times 1$ window where N is the license plate height. The hue value for each pixel is used to represent the color information and the intensity is to represent the texture information. The output of both the vertical and the horizontal scan is combined to find candidate regions. Time-delay neural network (TDNN) is implemented in [74] to extract plates. Two TDNNs are used for analyzing color and texture of the license plate by examining small windows of vertical and horizontal cross sections of the image.

In [75], the edge and the color information are combined to extract the plate. High edge density areas are considered as plate if their pixel values are the same as the license plate.

In [80], the statistical and the spatial information of the license plate is extracted using the covariance matrix. The

single covariance matrix extracted from a region has enough information to match the region in different views. A neural network trained on the covariance matrix of license plate and nonlicense plate regions is used to detect the license plate.

In [81], the rectangle shape feature, the texture feature, and the color feature are combined to extract the license plate. 1176 images that were taken from various scenes and conditions are used. The success rate is 97.3%.

In [43], the raster scan video is used as input with low memory utilization. Gabor filter, threshold, and connected component labeling are used to obtain plate region.

In [75], wavelet transform is used to detect edges of the image. After the edge detection, the morphology in image is used to analyze the shape and the structure of the image to strengthen the structure to locate the license plate.

In [76], a method applies HL subband feature of 2-D DWT twice to significantly highlight the vertical edges of license plates and suppress the background noise. Then, promising candidates of license plates are extracted by first-order local recursive Otsu's segmentation and orthogonal projection histogram analysis. The most probable candidate is selected by edge density verification and aspect ratio constraint.

In [77], the license plate is detected using local structure patterns computed from the modified census transform. Then, two-part postprocessing is used to minimize false positive rates. One is the position-based method that uses the positional relation between a license plate and a possible false positive with similar local structure patterns, such as headlights or radiators. The other is the color-based method that uses the known color information of license plates.

Reference [78] proposed a method using wavelet analysis and improved HLS color decomposition and Hough line detection.

G. Discussion

In this section, we described existing license plate extraction methods and classified them based on the features they used. In Table I, we summarize them and discuss the pros and cons of each class of methods.

In Table IV, we highlight some typical ALPR systems presented in the literature. The techniques used in the main procedures are summarized. The performances of license plate extraction using different methods are shown.

In the literature, experimentation setups are normally restricted to well-defined conditions, e.g., vehicle position and illumination. To overcome the problem of varying illumination, infrared (IR) units have been used. This method emerged from the nature of the license plate surface (retroreflective material) and has been already tested in the literature [63], [75], [82], [83]. In [75], a detection rate of 99.3% was achieved for 2483 images of Iranian vehicles captured using IR illumination units. IR cameras are also used in some commercial systems. An ALPR system [84] from Motorola and PIPS Technology acts as a silent partner in the vehicle, constantly scanning license plates of passed vehicles. When a vehicle of interest is passed, the system can alert the officer and record the time and GPS coordinates. The IBM Haifa Research Laboratory [85] developed an LPR engine for the Stockholm road-charging project. Nedap [86] automatic vehicle identification and vehicle access control applications claim that when installed properly an approximate 98% accuracy typically can be achieved. Geovision [87] license plate recognition system uses advanced neural networks technology to capture vehicle license plates. The system can reach up to 99% recognition success with high recognition speed (< 0.2 s). In [82], Naito *et al.* studied the ALPR problem from the viewpoint of the sensor system. The authors claimed that the existing dynamic range of a conventional CCD video camera is insufficient for ALPR purposes. Therefore, the sensor system is upgraded to a double dynamic range using two CCDs and a prism that splits an incident ray into two lights of different intensities. In testing, the input image is binarized using Otsu's method [88] and the character regions are extracted exploiting the focal length of the sensor to estimate the character size. Recognition rates are over 99% for conventional plates and over 97% for highly inclined plates from -40° to 40° . Regarding the camera-to-car distance, as reported in [4], license plate height should be at least 20–25 pixels to facilitate the character segmentation and recognition.

III. LICENSE PLATE SEGMENTATION

The isolated license plate is then segmented to extract the characters for recognition. An extracted license plate from the previous stage may have some problems, such as tilt and nonuniform brightness. The segmentation algorithms should overcome all of these problems in a preprocessing step.

In [51] and [89], the bilinear transformation is used to map the tilted extracted license plate to a straight rectangle.

In [90], a least-squares method is used to treat horizontal tilt and vertical tilt in license plate images.

In [91], according to Karhunen–Loeve transform, the coordinates of characters are arranged into a 2-D covariance matrix. The eigenvector and the rotation angle α are computed in turn. Then, image horizontal tilt correction is performed. For vertical tilt correction, three methods K-L transform, the line fitting based on K -means clustering, and the line fitting based

on least squares are put forward to compute the vertical tilt angle θ .

In [92], a line fitting method based on the least-squares fitting with perpendicular offsets was introduced for correcting a license plate tilt in the horizontal direction. Tilt correction in the vertical direction by minimizing the variance of coordinates of the projection points was proposed. Character segmentation is performed after horizontal correction and character points are projected along the vertical direction after shear transform.

Choosing an inappropriate threshold for the binarization of the extracted license plate results in joined characters. These characters make the segmentation very difficult [90]. License plates with a surrounding frame are also difficult to segment since after binarization, some characters may be joined with the frame [93]. Enhancing the image quality before binarization helps in choosing the appropriate threshold [93]. Techniques commonly used to enhance the license plate image are noise removal, histogram equalization, and contrast enhancement. In [93], a system was proposed to conduct gradient analysis on the whole image to detect the license plate and then the detected license plate is enhanced by grey level transformation. A method to enhance only the characters and to reduce the noise was proposed in [94]. The size of the characters is considered to be approximately 20% of the license plate size. First, the grey-scale level is scaled to 0–100, then the largest 20% pixels are multiplied by 2.55. Only characters are enhanced while noise pixels are reduced. Since binarization with one global threshold cannot always produce acceptable results, adaptive local binarization methods are normally used. In [95], local thresholding is used for each pixel. The threshold is computed by subtracting a constant c from the mean grey level in an $m \times n$ window centered at the pixel. In [96], the threshold is given by the Niblack binarization formula to vary the threshold over the image, based on the local mean and the standard deviation.

In the following, we categorize the existing license plate segmentation methods based on the features they used.

A. License Plate Segmentation Using Pixel Connectivity

Segmentation is performed in [12], [30], [52], and [97]–[99] 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.

B. License Plate Segmentation Using Projection Profiles

Since characters and license plate backgrounds have different colors, they have opposite binary values in the binary image. Therefore, some proposed methods as in [15], [21], [24], [32], [50], [51], [74], and [100]–[104] 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 [15], along with noise removal and character sequence analysis, vertical projection is used to extract the characters.

TABLE II
PROS AND CONS OF EACH CLASS OF LICENSE PLATE SEGMENTATION METHODS

Methods	Pros	Cons
Using pixel connectivity [12], [30]	Simple and straightforward, robust to the license plate rotation.	Fails to extract all the characters when there are joined or broken characters.
Using projection profiles [21], [24], [51], [101]	Independent of character positions, be able to deal with some rotation.	Noise affects the projection value, requires prior knowledge of the number of license plate characters.
Using prior knowledge of characters [6], [14], [105], [106]	Simple.	Limited by the prior knowledge, any change may result in errors.
Using character contours [107], [108]	Can get exact character boundaries.	Slow and may generate incomplete or distorted contour.
Using combined features [111], [112]	More reliable.	Computationally complex.

By examining more than 30 000 images, this method reached the accuracy rate of 99.2% with a 10–20 ms processing speed. In [51] and [101], character color information is used in the projection instead of using the binary license plate. 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. However, it depends on the image quality. Any noise affects the projection value. Moreover, it requires prior knowledge of the number of plate characters.

C. License Plate Segmentation Using Prior Knowledge of Characters

Prior knowledge of characters can help the segmentation of the license plate. In [14], 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.

In [6], the extracted license plate is resized into a known template size. In this template, all character positions are known. After resizing, the same positions are extracted to be the characters. This method has the advantage of simplicity. However, in the case of any shift in the extracted license plate, the extraction results in background instead of characters.

In [105], the proposed approach provides a solution for the vehicle license plates that are degraded severely. Color collocation is used to locate the license plate in the image. Dimensions of each character are used to segment the character. The layout of the Chinese license plate is used to construct a classifier for recognition.

The license plates in Taiwan are all in the same color distribution [106], i.e., black characters and white background. If the license plate is scanned with a horizontal line, the number of black to white (or white to black) transitions is at least 6 and at most 14. Hough transform is used to correct the rotation problem, the hybrid binarization technique is used to segment the characters in the dirty license plate, and feedback self-learning procedure is employed to adjust the parameters. In the experiment, 332 different images are used

captured under various illuminations and at different distances. The overall location and segmentation rates are 97.1% and 96.4%.

D. License Plate Segmentation Using Character Contours

Contour modeling is also employed for character segmentation. In [108] a shape driven active contour model is established, which utilizes a variational fast marching algorithm. The system works in two steps. First, rough location of each character is found by an ordinary fast marching technique [109] combined with a gradient-dependent and curvature-dependent speed function [110]. Then, the exact boundaries are obtained by a special fast marching method.

E. License Plate Segmentation Using Combined Features

In order to efficiently segment the license plate, two or more features of the characters can be used. In [111], an adaptive morphology based segmentation approach for seriously degraded plate images was proposed. An algorithm based on the histogram detects fragments and merges these fragments. A morphological thickening algorithm [113] locates reference lines for separating the overlapped characters. A morphological thinning algorithm [114] and the segmentation cost calculation determine the baseline for segmenting the connected characters. For 1189 degraded images, the entire character content is correctly segmented in 1005 of them.

In [115], a method was described for segmenting the main numeric characters on a license plate by introducing dynamic programming (DP). The proposed method functions very rapidly by applying the bottom-up approach of the DP algorithm and also robustly by minimizing the use of environment-dependent features such as color and edges. The success rate for detection of four main numbers is 97.14%.

F. Discussion

In this section, we described existing license plate segmentation methods and classified them based on the features they used. In Table II, we summarize them and discuss the pros and cons of each class of methods.

In Table IV, we highlight some typical ALPR systems presented in the literature. The techniques used in the main procedures are summarized. The performances of license plate segmentation using different methods are shown.

IV. CHARACTER RECOGNITION

The extracted characters are then recognized and the output is the license plate number. Character recognition in ALPR systems may have some difficulties. Due to the camera zoom factor, the extracted characters do not have the same size and the same thickness [30], [93]. Resizing the characters into one size before recognition helps overcome this problem. The characters' font is not the same all the time since different countries' license plates use different fonts. Extracted characters may have some noise or they may be broken [30]. The extracted characters may also be tilted [30].

In the following, we categorize the existing character recognition methods based on the features they used.

A. Character Recognition Using Raw Data

Template matching is a simple and straightforward method in recognition [5], [101]. 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 [90].

Template matching is performed in [5], [12], [30], [51], [93], and [116] after resizing the extracted character into the same size. Several similarity measuring techniques are defined in the literature. Some of them are Mahalanobis distance and the Bayes decision technique [30], Jaccard value [51], Hausdorff distance [116], and the Hamming distance [5].

Character recognition in [93] and [117] uses normalized cross 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 [90]. In [82], the problem of recognizing tilted characters is solved by storing several templates of the same character with different inclination angles.

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 [101]. 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 [90]. The extracted features form a feature vector which is compared with the pre-stored feature vectors to measure the similarity.

In [101] and [119], the feature vector is generated by projecting the binary character horizontally and vertically. In [119], each projection is quantized into four levels. In [102], the feature vector is generated from the Hotelling transform of each character. The Hotelling transform is very sensitive to the

segmentation result. In [120], 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 [97], 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 [121], 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. Then the number of transitions from character to background and spacing between them form a feature vector for each character. This method is invariant to the rotation of the character because the same feature vector is generated. In [122], the feature vector is generated by sampling the character contour all around. The resulted waveform is quantized into the feature vector. This method recognizes multifont and multi-size characters since the contour of the character is not affected by any font or size change. In [123], the Gabor filter is used for feature extraction. The character edges whose orientation has the same angle as the filter will have the maximum respond to the filter. This can be used to form feature vector for each character. In [124], Kirsch edge detection is applied on the character image in different directions to extract features. Using Kirsch edge detection for feature extraction and recognition achieved better results than other edge detection methods, such as Prewitt, Frei Chen, and Wallis [125]. In [126], the feature vector is extracted from the binary character image by performing thinning operation and then converting the direction of the character strokes into one code. In [127], pixels' grey-scale values of 11 subblocks as the features are fed into a neural network classifier. In [128], a scene is processed by visiting nonoverlapping 5×5 blocks, processing the surrounding image data to extract "spread" edge features based on the research conducted in [129], and classifying this subimage according to the coarse-to-fine search strategy described in [130]. In [49], three character features contour-crossing counts, directional counts, and peripheral background area are used. The classification is realized by a support vector machine. In [52], the topological features of characters—the number of holes, endpoints, three-way nodes, and four-way nodes—are used. These features are invariant to spatial transformations.

After feature extraction, many classifiers can be used to recognize characters, such as ANN [127], SVM [74], HMM [95]. Some researchers integrate two kinds of classification schemes [131], [132], multistage classification schemes [133], or a "parallel" combination of multiple classifiers [134], [135].

C. Discussion

In this section, we described existing character recognition methods and classified them based on the features they used. In Table III, we summarize them and discuss the pros and cons of each class of methods.

In Table IV, we highlight some typical ALPR systems presented in the literature. The techniques used in the main procedures are summarized. The performances of character

TABLE III
PROS AND CONS OF EACH CLASS OF CHARACTER RECOGNITION METHODS

Methods	Pros	Cons
Using pixel values	Template matching [5], [93], [117]	Simple and straightforward.
	Several templates for each character	Processing nonimportant pixels and slow, vulnerable to any font change, rotation, noise and thickness change.
Using extracted features	Horizontal and vertical projections [101], [119]	Be able to recognize tilted characters.
	Hotelling transform [102]	More processing time.
	The number of black pixels in each 3×3 pixels block [120]	Feature extraction takes time, nonrobust features will degrade the recognition.
	Count the number of elements that have certain degrees inclination [97]	
	The number of transitions from character to background and spacing between them [121]	
	Sampling the character contour all around [122]	
	Gabor filter [123]	
	Kirsch edge detection [124]	
	Convert the direction of the character strokes into one code [126]	
	Pixels' values of 11 subblocks [127]	
	Nonoverlapping 5×5 blocks [128]	
	Contour-crossing counts (CCs), directional counts (DCs), and peripheral background area (PBA) [49]	
	Topological features of characters including the number of holes, endpoints, three-way nodes, and four-way nodes [52]	

segmentation using different methods are shown when available with processing speed.

Some characters are similar in their shape, such as (B-8), (O-0), (I-1), (A-4), (C-G), (D-O), and (K-X). These characters confuse the character recognizer, especially when they are distorted. Dealing with this ambiguity problem should attract more attention than regular OCR in future research.

V. SUMMARY, FUTURE DIRECTIONS, AND CONCLUSION

A. Summary

In general, an ALPR system consists of four processing stages. In the image acquisition stage, some points have to be considered when choosing the ALPR system camera, such as the camera resolution and the shutter speed. In the license plate extraction stage, the license plate is extracted based on some features such as the color, the boundary, or the existence of the characters. In the license plate segmentation stage, the characters are extracted by projecting their color information, by labeling them, or by matching their positions with template. Finally, the characters are recognized in the character recognition stage by template matching, or by classifiers such as neural networks and fuzzy classifiers. Automatic license plate recognition is quite challenging due to the different license plate formats and the varying environmental conditions. There are numerous ALPR techniques that have been proposed in recent years. Table IV highlights some typical ALPR systems performance as presented in the literature. Issues, such as main processing procedure, experimental database, processing time, and recognition rate, are provided. However, the authors of [4] pointed out that it is inappropriate to explicitly declare which methods demonstrate the highest performance since there is a lack of uniform way to evaluate the methods. Therefore, in [4],

Anagnostopoulos *et al.* provided researchers with a common test set to facilitate the systematic performance assessment.

B. Current Trends and Future Directions

Although significant progress of ALPR 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 ALPR system should have the ability to deal with multistyle plates, e.g., different national plates with different fonts and different syntax. Little existing research has addressed this issue, but still has some constraints. In [127], four critical factors were proposed to deal with the multistyle plate problem: plate rotation angle, character line number, the alphanumeric types used and character formats. Experimental results showed 90% overall success in a data set of 16 800 images. The processing speed using the lower resolution images is about 8 f/s. Reference [136] also proposed an approach that can deal with various national plates. The optical character recognition is managed by a hybrid strategy. An efficient probabilistic edit distance is used for providing an explicit video-based ALPR. Cognitive loops are introduced at critical stages of the algorithm.

In most ALPR systems, either the acquisition devices provide still images only, or only some frames of the image sequence are captured and analyzed independently. However, taking advantage of the temporal information of a video can highly improve the system performance. Basically, using the temporal information consists of tracking vehicles over time to estimate the license plate motions and thus to make the recognition step more efficient. There are two kinds of strategies to achieve that goal. One strategy is using the tracking output to form a high resolution image by combining multiple,

TABLE IV
PERFORMANCE COMPARISON OF SOME TYPICAL ALPR SYSTEMS [LICENSE PLATE EXTRACTION (LPE), LICENSE PLATE SEGMENTATION (LPS), OPTICAL CHARACTER RECOGNITION (OCR)]

Methods	Main Procedures			Database Size	Image Conditions	LPE Rate	LPS Rate	OCR Rate	Total Rate	Processing Time	Real Time	Plate format
	LPE	LPS	OCR									
[2]	Matching of vertical edges	Vertical projection	Template matching on hamming distance	610 images	640 × 480 pixels, various illumination conditions, some angle of view and dirty plates	96.2%	–	–	95%	–	–	Saudi Arabian plates
[8]	Vertical edges	–	–	1165 images	384 × 288 pixels	~100%	–	–	–	47.9 ms	Yes	Chinese plates
[18]	Block-based processing	–	Template matching	180 pairs of images	Multiplates with occlusion and different sizes	94.4%	–	95.7%	–	75ms for LPE	Yes	Taiwanese plates
[20]	Hough transform and contour algorithm	Vertical and horizontal projections	Hidden Markov model (HMM)	805 images	800 × 600 pixels, different rotation and lighting conditions	98.8%	97.6%	97.5%	92.9%	0.65 s for LPE and 0.1 s for OCR	No	Vietnamese plates
[21]	GST	–	–	330 images	Various viewing directions	93.6%	N/A	N/A	N/A	1.3 s	No	Korean plates
[22]	Edge detection and vertical and horizontal projections	Vertical and horizontal projections	Back propagation neural network	12 s video	320 × 240 pixels	–	–	–	85.5% and ~ 100% after retraining	100 ms	Yes	Taiwanese plates
[5]	Edge statistics and morphology	–	–	9825 images	768 × 534 pixels, different lighting conditions	99.6%	–	–	–	100 ms	Yes	Chinese plates
[26]	CCA	–	–	4 hrs + video	320 × 240 pixels, degraded low resolution video	96.6%	–	–	–	30 ms	Yes	Taiwanese plates
[49]	VQ	–	–	300+ images	768 × 256 pixels, different brightness and sensor positions	98%	–	–	–	200 ms	No	Italian plates
[50]	SCW	SCW	Two-layer probabilistic neural network	1334 images	Different background and illumination	96.5%	–	89.1%	86%	276 ms (111 ms for LPE, 37 ms for LPS, and 128 ms for OCR)	Yes	Greek plates
[52]	Gabor filter	Local vector quantization	–	300 images	fixed angle and different illumination	98%	–	94.2%	–	3.12 s	No	Multinational
[42]	WT	–	–	315 images	600 × 450 pixels, different illumination and orientation	92.4%	–	–	–	–	–	Taiwanese plates
[57]	Haar-like features and AdaBoost	–	–	–	640 × 480 pixels, live video	95.6%	–	–	–	–	–	American plates
[53]	Local Haar-like features and AdaBoost	–	–	160 images	648 × 486 pixels, various conditions and view angles	93.5%	–	–	–	80 ms	Yes	Australian plates
[58]	Haar-like features and cascade AdaBoost	Peak-valley analysis	SVM based on CCs, DCs, and PBA	11 896 images	640×480 pixels, different format, size and lighting conditions	99.6%	–	–	98.3%	30 ms	Yes	Taiwanese plates

[62]	Color and fuzzy aggregation	Connected component and blob coloring	Self-organizing character recognition	1088 images	Various scene and conditions	97.9%	–	95.6%	93.7%	0.4 s for LPE and 2 s for OCR	No	Taiwanese plates
[71]	Color, Mean Shift	–	–	57 images	324 × 243 pixels	97.6%	–	–	–	6 s	No	Australian plates
[75]	Horizontal scan of repeating contrast changes	Lateral histogram analysis.	Fully connected feedforward artificial neural network with sigmoidal activation functions	–	–	99%	–	98%	80%	15 s	No	Italian plates
[82]	Color, texture and TDNN	TDNN	SVM	400 video clips	640 × 480 pixels	97.5%	–	97.2%	–	1 s	No	Korean plates
[85]	Rectangular shape, texture, and color features	Feature projection	Template matching	1176 images	640 × 480 pixels, various scenes and conditions	97.3%	95.7%	–	93.1%	220 ms for LPE and 0.9 s for OCR	No	Chinese plates
[83]	IR	–	–	2483 images	Various illumination, shadow, scale, rotation, and weather conditions	99.3%	–	–	–	300 ms	No	Iranian plates
[86]	2 CCDs and a prism	–	Template matching and normalized cross correlation	1000 images	Various illumination conditions	–	–	–	99% (conventional) 97% (highly inclined)	–	–	Japanese plates
[93]	Gradient analysis	–	Normalized cross correlation & grey-level template matching	2340 images	Different weather and illumination conditions	–	–	98.6%	91.1%	1.1 s	No	Italian plates
[109]	Scan line, texture properties, color, and Hough transform	Hybrid binarization, feedback self learning	–	332 images	867 × 623 pixels (various illumination and different distances)	97.1%	96.4%	–	–	0.53 s for LPE and 0.06 s for LPS	No	Taiwanese plates
[14]	–	Scan line and vertical projection	–	30000+ images	Titled	–	99.2%	–	–	10–20 ms for LPS	Yes	Chinese plates
[115]	–	Mathematical morphology and adaptive segmentation and fragment merging	–	1189 images	Degraded with fragmented and connected characters	–	84.5%	–	–	–	–	Japanese plates
[106]	Corner detection and template matching	Vertical and horizontal projections	Hottelling transform and Euclidean distance	1000+ images	439 × 510 pixels	–	–	–	99.6%	–	–	Dutch plates
[108]	Prior knowledge of color collocation	Prior knowledge of character dimensions	Improved back propagation neural network and prior knowledge of the plate layout	–	–	–	–	97.7%	–	–	–	Chinese plates

subpixel shifted, low-resolution images. This technique is known as super-resolution reconstruction [137]. Reference [138] proposed to detect the license plate using an AdaBoost classifier, and to track it using a data-association approach. Reference [143] proposed a new reduced cost function to produce images of higher resolution from low resolution frame sequences. It can be employed for real time processing.

Alternative to super-resolution techniques, we can merge the high-level outputs of the recognition to make a final decision. For example, in [139], the authors presented a real-time video-based method utilizing post-processing of Kalman tracker. In this paper, Viola-Jones' object detector is used to detect the plate position. The support vector machine is used to recognize characters. To fully make use of the video information, a Kalman tracker is used to predict the plate positions in the subsequent frames to reduce the detector searching area. The

final character recognition also uses the interframe information to enhance the recognition performance.

The resolution of current ALPR video cameras is low. Recently, high definition cameras are adopted in license plate recognition systems since these cameras preserve object details at a longer distance from the camera. However, due to the large amount of information to be processed, the computational costs are high. To address this issue, Giannoukos *et al.* [140] introduced a scanning method, operator context scanning (OCS), which uses pixel operators in the form of a sliding window, associating a pixel and its neighborhood to the possibility of belonging to the object that the method is searching. This OCS method increases the processing speed of the original SCW method by 250%.

In [141], on the basis of existing local binary pattern operator, the authors proposed a low-computational advanced

linear binary pattern operator as feature extraction for low-resolution Chinese character recognition of vehicle license plate. Reference [142] also proposed a recognition method of blurred vehicle license plate based on natural image matting.

Segmentation and recognition are two important tasks in ALPR. Traditionally, these two tasks were implemented in a cascade fashion independently and sequentially [145]. Recently, there has been an increasing interest in exploring the interaction between the two tasks. For example, the prior knowledge on the characters to be recognized is employed for segmentation [144] and the recognition outputs are fed back to the segmentation process [52]. Reference [145] proposed a two-layer Markov network to formulate the joint segmentation and recognition problem in a 1-D case. Both the low-level features and high-level knowledge are integrated into a two-layer Markov network where the two tasks are achieved simultaneously as the results of the belief propagation inference.

Recently, license plate recognition has also been used for vehicle manufacturer and model recognition [146], [147].

There are many other open issues for the future research.

- 1) The technical specifications of video surveillance equipment vary as older systems may be equipped with low resolution black and white cameras, and newer systems are likely to be equipped with high resolution color cameras. An effective ALPR system should be able to integrate with varying existing surveillance equipment.
- 2) For video-based ALPR, we need to first extract the frames that have the passing cars. It needs either frame differencing or motion detection. Extracting the correct frame with a clear car plate image is another challenge, especially when the car speed is very fast, violating the speed limit.
- 3) To deal with the illumination problem, good pre-processing methods (image enhancement) should be used to remove the influence of lighting and to make the license plate salient.
- 4) New sensing systems that are robust to the change of illumination conditions should also be used to elevate the ALPR performance.
- 5) For optical character recognition, future research should concentrate on improving the recognition rate on ambiguous characters, such as (B-8), (O-0), (I-1), (A-4), (C-G), (D-O), (K-X), and broken characters.
- 6) To evaluate the performance of different ALPR systems, a uniform evaluation way is needed. Besides a common test set, we also need to set some regulations for performance comparison, such as how to define the correct extraction of license plate, what is the successful segmentation, how to calculate the character recognition rate. Here, we suggest that the plate extraction is successful when all characters on it are shown; the character segmentation is successful when the character image encloses the whole character; and the character recognition is successful when all the characters on a plate are correctly recognized.

C. Conclusion

This paper presented a comprehensive survey on existing ALPR techniques by categorizing them according to the features used in each stage. Comparisons of them in terms of pros, cons, recognition results, and processing speed were addressed. A future forecast for ALPR was also given at the end. The future research of ALPR should concentrate on multistyle plate recognition, video-based ALPR using temporal information, multiplates processing, high definition plate image processing, ambiguous-character recognition, and so on.

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