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Systematic review on vehicular licence plate recognition framework in intelligent transport systems

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Abstract: In recent years, vehicular licence plate recognition (VLPR) framework has emerged as one of the most significant issues in intelligent transport systems. It has emerged as an important and complicated issue of research in recent times as explorations are carried on this issue with regard to the challenges and diversities of licence plates (LP) including various illumination and hazardous situations. Restricted situations like stationary background, only one vehicle image, fixed illumination, and limited vehicular speed have been focused in most of the approaches. VLPR approaches should be generalised for being capable of identifying LP containing different fonts, colours, languages, complex backgrounds, deformities, hazardous situations, occlusion, speeding vehicles, vertical or horizontal skew, blurriness, and illumination diversions. A comprehensive investigation on the existing VLPR techniques has been carried throughout this study by the aspects of detecting, segmenting, and recognising the plates. Different existing VLPR approaches have been categorised in accordance with the deployed attributes and the classifications have been compared as well on the basis of conveniences, inconveniences, processing time, and recognition rate when available.

1 Introduction

Vehicular licence plate recognition (VLPR) framework has emerged as a core methodology for ensuring the traffic applications and security ranging from parking lot access monitoring to vehicle surveillance, automatic toll collection, road traffic monitoring, vehicular law enforcement, calculating the traffic volume, vehicle activity analysis, tracking for safety, and criminal pursuits [1, 2]. This identifies the exact plate number of the vehicle from frame sequences (video) or still images. It is known as the automatic car plate recognition, vehicular number plate identification, and optical character recognition (OCR) for vehicles as well where several techniques, for example, image processing, object identification, and pattern recognition, get combined for fulfilling this framework.

For fulfilling the requirements of intelligent transport systems (ITS), the VLPR systems should be real time or operate properly with less processing time where ‘real time’ denotes the operations of tracking every expected single object throughout the image with fast processing. The VLPR framework generally comprises four processing steps [3] such as image acquisition, detection of the vehicular LP (licence plate), segmentation of the LP, and recognition of the LP characters.

In the acquisition stage, the vehicle image is collected by utilising cameras. For proper processing of this stage, some features associated with the camera such as resolution, camera type, orientation, light, lens, and shutter-speed should be taken into account. The last three stages are the most crucial for determining the performance of the whole framework. The detection of LP is the substantial part of the framework [3] because the segmentation and recognition performances are greatly influenced by the success of this stage. There are many critical issues that hamper the stages of the VLPR framework for which the overall performance of the system may fall. The system performance depends on the individual stage's robustness.

The existing VLPR research works have been surveyed in this paper systematically and the existing procedures have been categorised (Fig. 1) in accordance with the individually utilised attributes, convenience, and inconveniences. The available recognition performances, platform for each procedure, and processing time have also been reported. Some major challenging issues, procedures to cope with the issues including with available performance rates and some suggestions on the topics which should be taken into account have been addressed as well for future aspects.

This paper has been methodised as follows aiming to represent an updated, critical, and comprehensive analysis on VLPR framework. Firstly, a comprehensive review on the detection methods of the vehicular LP and classification of the methods according to utilised attributes has been presented in Section 2. In Section 3, the segmentation procedures and classification have been discussed. The methods on recognition of LP characters and classification of the methods according to the implemented features have been presented in Section 4. Finally, the paper has been concluded in Section 5 with discussion and future work.

2 Vehicular plate detection

The precision of the VLPR framework is largely influenced by the vehicular plate detection stage. The existing detection methods are categorised according to the utilised attributes as described below.

2.1 Texture attributes

Texture is the changing of colour taken place between the background and the consisting characters of the vehicular LP. The methods based on texture attributes differentiate the momentous shift of grey level that occurs between the background and the consisting characters of the vehicular LP.

Owing to this texture transition, a region consisting of relatively higher edge density is observed. Various techniques have been implemented in [4, 5]. Owing to the shifting in the grey level, there arise drastic peaks through the scanned line and this scan line procedure has been implemented in [4, 6]. An overall detection rate of 94% has been reported in [7] by utilising frequency domain masking integrated with a better contrast enhancement procedure along with the statistical process of binarisation for vehicular images under various hazardous situations. A robust procedure of AdaBoost (adaptive boosting) cascades integrated with a three-

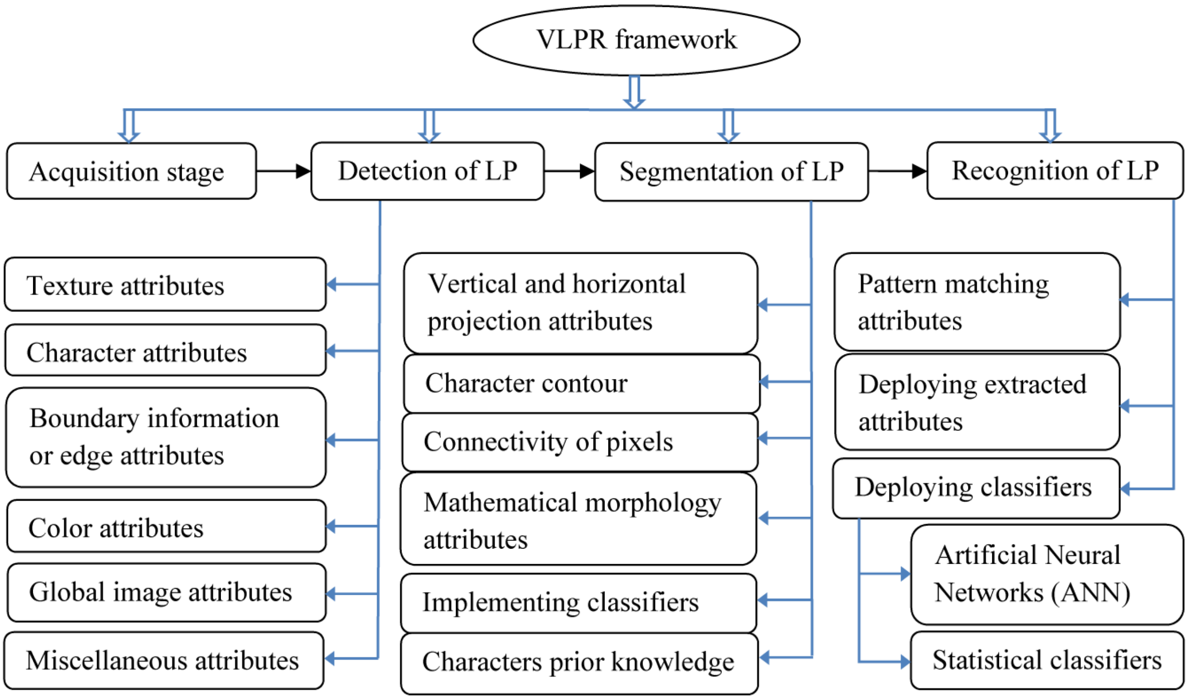

Fig. 1 *Basic categorisation of VLPR framework*

layer local binary pattern classifiers has been implemented in [8] and a relatively higher detection accuracy of 98.56% has been reported. A success rate of 98% has been reported in [9] where the input images consist of a specific and fixed orientation angle. However, the procedure has been reported as time-consuming. Another procedure of Daubechies wavelet transforms technique that utilises a discrete single-level two-dimensional wavelet transform has been utilised in [10] and reported a better detection accuracy of 97.33%. The procedures based on the texture attributes have an egregious characteristic of extracting the plate region of vehicular image, although there is deformed boundary. However, for the case of complex background images, especially where exists a lot of edges or various illumination situations, these techniques can be found as relatively complex computationally.

2.2 Character attributes

The procedures based on the character attributes have the characteristic of determining the probable plate region by localising the character positions in the image by scanning the image for finding the character existence and when the character existence is found then the corresponding region gets detected for possessing the probable plate region. The method of calculating the differences between the background region and the character zone along with identification of character-width has been utilised in [11] in order to recognise the character region first. Finally, the procedure yields a prominent detection rate which is 99.5% through enumerating the inter-distances among the characters. By using the first layer classifier, the primary set of the probable character region is achieved in [12] and later by using the second layer classifier results in discarding the non-character region. For the first layer classifier, Adaboost classifiers (36) have been utilised, whereas a support vector machine (SVM) technique implemented with the scale-invariant feature transform feature descriptors has been utilised at the second layer. A cost-effective histograms of oriented gradients-based detection procedure with an accuracy of over 96% has been proposed in [13].

In order to identify the characters properly on the plate image, these techniques need to undergo through binarisation process that happens by changing the grey-scale values of the image into binary. Furthermore, these techniques are non-robust for the case of existing extra text characters in the input image other than the desired characters. All the binary objects get processed here which results in much more processing time.

2.3 Boundary information or edge attributes

Generally, vehicular plates holding licence information possess the shape of quadrangles along with particular aspect ratio. As a result, the probable candidate region can be detected by scanning for the probable rectangular shapes that exist in the vehicular images. In order to locate this quadrangles or rectangular shape, these boundary information-based techniques have been widely utilised in [14–17]. The boundaries of these vehicular plates holding licence information can be expressed through the edge density of the image because of the colour alteration that takes place between the vehicle body and the LP. Sobel filters have been utilised in [18–21] in order to extract this edge information. The process of detecting this edge horizontally results in identifying the dual horizontal lines, whereas the detection technique of this edge vertically results in identifying the dual vertical lines. As a result, the probable candidate quadrangles get detected after both of the edges had been detected simultaneously. A novel approach of vertical edge detection algorithm (VEDA) has been proposed in [22] because of the extraction of this plate region. The procedure of implementing this VEDA has been noticed with a significant less processing time about five to nine times less than the existing procedures that have implemented the Sobel operators.

Here, in [23–25], candidate regions have been generated through utilising the vertical edge information for matching. On the other hand, the horizontal edge magnitude has been proven to be non-robust attribute for determining this candidate region because of bringing errors for the vehicle bumpers [14].

These edge-based procedures are relatively simpler in accordance with other techniques to implement with faster processing time. A relative comparison of the edge-based algorithms has been depicted in Table 1.

2.4 Colour attributes

Vehicular LPs colour has been considered as one of the very important attributes because there are some particular colour codes for the LP in accordance with jurisdictions under different states, provinces, or countries. Therefore, some methodologies which have been reported here involve in locating the colour features in order to localise the probable plate region from the image. The colour combination between the characters and the vehicular plates is a unique feature, whereas this colour combination takes place, especially in the candidate plate region. A detection technique has been implemented in [30] based on this basic concept. According to the vehicular inspection and regulation rules in People's Republic of China, the LP attains rectangular shape consisting seven characters, whereas yellow coloured plates are maintained by the heavier vehicles and blue coloured plates are allotted to the relatively lighter vehicles. In accordance with this plate format, a technique has been utilised here where the input image pixels get classified into 13 categories through utilising the hue, lightness, and saturation (HLS) colour model. A neural network implemented the procedure for the classification of the each pixels colour information has been utilised in [31] where before this classification, the RGB constituents had been converted into HLS model. For determining the region that contains the largest density, the colour of the vehicular plates had been projected in accordance with vertical and horizontal orientation which finally confirmed the probable candidate region. Another candidate region detection procedure has been introduced in [32] on the HSI-based colour model integrated with adaptation to selection of statistical threshold. This procedure detects the vehicular candidate region in the case of the vehicle plate and vehicle bodies contain the identical colour. The yellow and green coloured candidate plate pixels can be detected through utilising the standard and mean deviation values of hue. On the other hand, the white, yellow, and green coloured candidate plate pixels can be detected through utilising those deviations of saturation along with intensity.

2.5 Global image attributes

Connected component analysis (CCA) is an image processing application in which the image is scanned first and the corresponding pixels are then labelled into components in accordance with the pixel connectivity [33]. For the processing of the binary images, this CCA integrated technique has been implemented as one of the significant methodologies [34–36].

For tracking out the connected objects, in [37], an algorithm has been implemented through utilising the contour detection. The objects that get selected to be the desired candidate within these connected objects possess the identical geometrical attributes as that of the vehicular plate. On the other hand, because of using images having bad qualities, this algorithm might end in distorted contours resulting in failure. Some other parameters like spatial measurements; for instance, aspect ratio and area are also widely utilised in [38, 39] in the case of tracking out this desired plate candidate. Another procedure of connected component labelling integrated with Euler number computation has been introduced in [40]. These two functions are simultaneously performed over the image in order to identify the position of hole first in binary image during the scanning of connected component labelling. From binary images, the connected component number, number of holes, and the Euler number gets enumerated efficiently for different types of images, and the outcome proves this algorithm to be much more proficient than the conventional procedures for simultaneous labelling of connected components and the Euler number computation.

2.6 Miscellaneous attributes

To strengthen the rate of detection of vehicular plates, miscellaneous attributes have been implemented by few procedures. These are the hybrid methods for the detection of vehicular LPs. A hybrid procedure with combined colour information and edge attributes has been implemented in [41] for the desired plate candidate detection. The pixel values of those regions, having higher edge densities and which are identical to the plate, get considered to be the probable candidate region.

In order to detect the required edges from the image, a wavelet transform technique has been utilised here. For analysing the correct structures and shapes of the image, the image morphology was utilised after the edges had been detected resulting in transforming the method to be more robust for localising the desired candidate region. Another hybrid procedure with combined colour information and texture attributes has been implemented in [42–45]. In [46], the quadrangular shape attribute combined with colour information and texture features has been implemented in order to track the plate region. A better rate of detection (97.3%) of images under different illumination situations has been reported for 1176 vehicular images captured from different scenes. A novel MD-YOLO framework integrated with convolutional neural network (CNN) has been implemented in [47] for the multi-directional LP detection which is capable of solving rotational problems elegantly by utilising proper prediction of rotation angles in real time. However, the images under terrible illumination, occlusion, and lower resolution are not highlighted here.

Table 1 Relative comparison of the boundary information or edge-based procedures

Edge algorithms	References	Accuracy rate, %
Sobel vertical	[20]	99.9
Robert and Rank	[26]	90
VEDA	[22]	91.4
Sobel	[19]	96.4
Prewitt	[17]	96.75
edge mapping and smoothing filter	[27]	96
Sobel vertical	[18]	97.78
VEDA	[28]	96
edge mapping and edge statistical analysis	[15]	99.6
Prewitt	[29]	95.33

2.7 Discussion

The most substantial stage of the total framework is the vehicular plate detection stage because without correct detection, the identification of vehicular plate number is not possible [3]. For this reason, if each pixel of the input image are processed then it would be much more time-consuming. Therefore, if the image is processed by utilising few salient attributes then it would be easier to detect the correct locus of vehicular LP resulting in decreasing the processing time as well. The methodology, conveniences, and inconveniences of the each class of attribute have been discussed in a nutshell in Table 2.

3 Segmentation of vehicular LP

Segmentation has become one of the very important topics recently in image processing field which involves in finding the meaningful, necessary information through processing an image properly, whereas the meaningful desired region contains higher order of desired data. Owing to extracting the desired characters from the detected vehicular plate for recognition, the isolated vehicular LP image needs to be segmented. However, in the previous processes, the detected vehicular LP might possess some complications like non-uniform brightness, angular skew of the LP vertically or horizontally. Before stepping into this segmentation stage, all this complications need to be solved through implementing proper pre-processing techniques for better extraction of the desired characters.

A modified local binarisation procedure of determining threshold values for individual character regions has been implemented in [55]. For finding out the missing or splitted characters, the pixel accumulating histogram analysis for individual character regions has been performed horizontally. For this reason, the region gets partitioned into two subregions and for these new regions, the threshold values are re-designated. Comparing to the local binarisation procedures, a 5% enhancement has been reported here. The binarisation outcome after implementing global thresholds and adaptive thresholds are depicted in Fig. 2.

A bilinear transform-based technique has been implemented in [31, 56] where for tilt adjustment, the extracted skewed vehicular LP is mapped into a straight quadrangle through utilising this bilinear transformation. Another procedure of tilt adjustment based on the radon transformation has been introduced in [57] where the image intensities are projected along the radial line that is oriented at a particular rotation angle for plate recognition at the odd angles. According to a horizontal scale, the image gets rotated after the

Table 2 Relative comparison of the existing detection methods with respect to the attributes

Class	Conveniences	Inconveniences	Reference	Accuracy
texture attributes	capable of detecting deformed boundaries for utilising LP's frequent colour transitions	higher processing time and processing complexity for multiple edges	[48], [49]	93.5%, 99%
character attributes	robustness even in rotation for utilising LP characters	higher processing time as processes all binary objects. Error happens if image possesses other text	[11], [50]	99.5%, 99%
boundary information or edge attributes	relatively faster and simpler for implementing the rectangular boundary attributes for LP	sensitivity to the unwanted edges. Error occurs for complex images	[51], [17]	98.8%, 96.75%
colour attributes	capable of detecting LPs containing deformities and skew as utilises LP's specific colour information and different illumination situations	HLS model has noise sensitivity, limitation of RGB due to illumination situations	[52], [53]	98%, 95.6%
global image attributes	independent of LP position because approach investigates the connected objects having identical dimension of LPs, straightforward approach	sometimes broken objects might be generated	[38], [34]	96.62%, 96.6%
miscellaneous attributes	robust and reliable because combined implementation of attributes increases effectiveness	not cost-effective as computationally complex approach	[46], [54]	97.3%, 97.5%

Fig. 2 *Plate images of noisy, after global and adaptive thresholding from left to right [55]*

Fig. 3 *Sequence of segmentation and merging of the initially broken characters from left to right [36]*

orientation angle had been determined through the algorithm. Finally, the rotational noise is reduced by utilising median filtering resulting in a relatively better performance including 98% accuracy rate for ∼1110 vehicular plate images under different environmental situations.

The existing segmentation methods are categorised according to the utilised attributes as given below.

3.1 Vertical and horizontal projection attributes

After implementing the binarisation process, in the binary output image, the binary values become inverse for the LP characters and the plate backgrounds because the backgrounds and the characters possess different colours. In order to segment these characters, vertical and horizontal projection-based techniques have been widely utilised in [10, 58, 59].

In order to identify the opening points and the finishing points of the characters, the binary output of the extracted desired plate region gets projected vertically first. After that, the detected vehicular LP gets projected in the horizontal direction because of extracting the individual characters. Sometimes the binary output of the plate images are not utilised in the case of segmentation, rather the colour information of the characters is used. The colour information of characters-based projection procedure has been utilised in [31, 60] rather than the binary plate images. One of the important advantages of this projection attribute-based method is that the character extraction process does not depend on the character positions and also functional for the little tilted vehicular LP images. As any observance of noise in the image may affect the projection procedure badly, noise removal techniques help for getting better performance. Overall, this procedure based on the exploitation of character pixels through horizontal and vertical projection scheme is relatively simpler and widely implemented.

3.2 Character contour attributes

For segmenting the characters of the LP images, this character contour feature is implemented as well. An active contour process integrated with shape-driven feature has been utilised in [61] which implements alternative matching algorithm that is relatively faster. This procedure operates based on two stages. First of all, a relatively faster and simpler matching algorithm [62] which is integrated with a speed function [63] that is curvature-dependent and gradient-dependent has been implemented in order to track out the rough locations of the individual characters. After that, a particular marching procedure which is relatively faster and dependent on the shape similarity, curvature, and gradient information gets implemented resulting in the extraction of the exact boundaries. Fig. 3 illustrates the sample of broken characters initially and the merged segmented final outcomes.

3.3 Connectivity of pixels

The attribute of connectivity of pixels has also been implemented for segmenting the characters of the LP images. Vehicular plate images are processed through binarisation process. After that from these binary vehicular plate images, the connectivity of pixels gets explored and labelled. Based on this labelled connected pixels, the segmentation procedure of characters has been carried through [34, 52, 64]. After analysing the labelled pixels, the aspect ratio and sizes of the characters are then explored. The characters possessing identical aspect ratio and size get finalised to be the expected vehicular LP characters. These techniques based on connectivity of pixels have some conveniences such as straightforwardness, robustness to the rotation of the vehicular number plates, and simplicity. However, in the case of the broken and joined characters, this procedure lapses in extracting all the characters.

3.4 Mathematical morphology attributes

For segmenting the characters of the LP images proficiently, this mathematical morphology feature is implemented as well [65]. A thoroughly dedicated character segmentation procedure has been implemented in [66] which is based on an adaptive segmentation technique integrated with morphological processing. This technique emphasises on the vehicular plate images with severe degradation. The fragments get detected by histogram projection-based algorithm and after that the fragments get merged. The

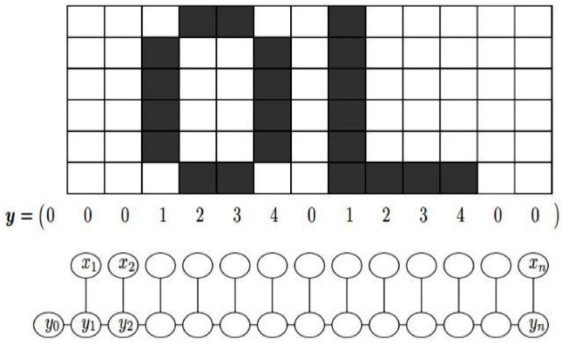

Fig. 4 *HMC model for LP image alignment [69]*

Fig. 5 *Hough transform for skew correction from left to right [71]*

Fig. 6 *Hybrid binarisation: solving dirt problems [71]*

identification of noise gets accomplished by performing morphological thinning and morphological thickening operation on the binary image. The baseline is determined for the segmentation of connected characters through segmentation cost enumeration and morphological thinning algorithm. The overlapped characters get separated by locating the reference lines through the morphological thickening algorithm [67]. The system results in segmenting the total character contents of 1005 degraded plate samples accurately out of a test sample of 1189 degraded vehicular plate images. A novel dynamic programming (DP)-based procedure has been introduced in [68] for the segmentation of the main four (numeric) characters on the LP image. The functionality of the procedure gets optimised through describing the threshold difference, the character alignments, and the interval distributions among the characters which has been utilised for extracting the character blobs. This DP algorithm-based procedure operates relatively faster because of implementing the bottom-up approach. A relatively better performance including 97.14% detection accuracy rate for the main four (numeric) characters has been reported.

3.5 Implementing classifiers

In order to segment the characters of the vehicular LP images proficiently, this classifiers are implemented as well. A character segmentation procedure for the low-resolution and noisy vehicular plate images based on the hidden Markov chains (HMC) integrated with estimation of the maximum a posteriori (MAP) has been implemented in [69]. For modelling the stochastic pattern between the segmentation of characters and the input images, HMC has been deployed (see Fig. 4). The segmentation problem has been revealed here as maximising a posteriori calculation from an admissible segmentation set. The procedure has been reported to be capable of segmenting the characters of Czech Republic LPs correctly in spite of possessing very poor quality. The proposed algorithm has been executed on the set of 1000 image samples which were collected from an LPR system with real-life capture along with 3.3% error rate.

3.6 Characters prior knowledge

The attribute of prior knowledge of the characters has been implemented as well for segmenting the characters of the LP images. A procedure based on the colour collocation scheme has been implemented in [70] for locating the vehicular number plates from the images. This technique emphasises on providing a solution for the vehicular plate images with severe degradation. For segmenting the characters, the dimensional prior knowledge of individual character has been utilised here. Finally, for recognition of the characters, a classifier has been constructed by utilising the Chinese vehicular LP layouts.

A hybrid binarisation-based procedure integrated with Hough transform method after horizontal scan line analysis on the vehicular LP images has been implemented in [71] in order to cope with the dirt and rotation problems because the character segmentation performance gets influenced basically by these two factors. For the corrective adjustment of the rotation problem of the vehicular plate images, the Hough transform technique has been utilised (see Fig. 5).

There are some particular colour codes for the LP in accordance with jurisdictions under different states, provinces, or countries, i.e. according to the vehicular inspection and regulation rules in Taiwan, the background colour of the LP is white containing black characters. For solving the problems associated with dirty number plates, the hybrid binarisation with feedback self-learning has been deployed (see Fig. 6). For the 332 vehicular images with different illumination situations, an overall localisation rate of 97.1% and character segmentation rate of 96.4% have been reported for this procedure.

Another approach of segmenting the characters utilising the information of known template sizes has been implemented in [72] where the extracted vehicular LP gets resized according to this template size. All these character positions in this template are predetermined. The identical positions are then extracted to be finalised as the expected characters after resizing. This procedure possesses the convenience of relatively simpler implementation. The major drawback of this procedure occurs when the extracted vehicular LPs experience any shifting. This method fails in extracting the expected characters for this reason and the background gets extracted rather.

3.7 Discussion

The proper segmentation rate has a great impact on the next stage, i.e. recognition of the characters because the majority of the recognition errors happen due to the segmentation errors rather than because of the missing recognition power. As a result for ensuring the better segmentation performance, some complications associated with the detected LP image like non-uniform brightness, angular skew of the LP vertically or horizontally, unpredictable shadows, physical damage, and dirt problem need to be properly treated. Based on the utilised attributes, the existing segmentation procedures have been classified here. The methodology, conveniences, and inconveniences of the each class of attribute have been discussed in a nutshell in Table 3.

4 Recognition of vehicle LP characters

In VLPR framework, in which stage, the extracted characters get identified by means of showing the expected plate numbers of the input vehicular LP images as the output is called the character recognition stage. This stage plays a very significant role in identifying the number of the LP.

In many cases, the extracted vehicular plate characters differ from being uniform thickness [77] and size with regard to the zoom factor of the camera. In order to get over this hindrance before recognition, the extracted characters need to be resized into one identical size. Moreover, the font size of the characters varies from country to country because different countries have their own font sizes. As a result, the characters' font does not remain identical all the time. On the other hand, the extracted characters might possess some noise or the characters might be broken. These extracted characters might be tilted as well [77]. Sometimes, the LP might possess unwanted information, i.e. it might possess colours or pictures which never provide any meaningful information with regard to identify the number of the LP. This type of images needs to be processed for normalisation and reduction in noise first [78].

Table 3 Relative comparison of the existing segmentation methods with respect to the attributes

Class	Conveniences	Inconveniences	Reference	Accuracy
vertical and horizontal projection attributes	character position independent and robust in slightly rotation	vertically and horizontally projected values might get affected by noise; character dimension-related prior knowledge is required	[73], [10]	99.2%, 95.93%
character contour attributes	extraction of exact boundaries of the characters is possible	distorted, imperfect, and partial contour dimensions might get produced and will slow down the performance	[25], [58]	90%, 91%
connectivity of pixels	robustness for the LPs having skew, relatively simpler procedure	in the case of broken or mutually joined characters, the character extraction may lapse	[52], [74]	93.7%, 97.2%
mathematical morphology	more robust and reliable due to combined morphology	higher processing time for computational complexity	[68], [66]	97.14%, 84.5%
implementing classifiers	real-time application, advanced and robust computational intelligence architecture	error might occur for broken or mutually joined characters, computational complexity	[69], [75]	96.7%
characters prior knowledge	relatively simpler and straightforward procedure	limited implementation depending on the prior knowledge and error might occur in the case of any alteration	[71], [76]	96.4%, 99.2%

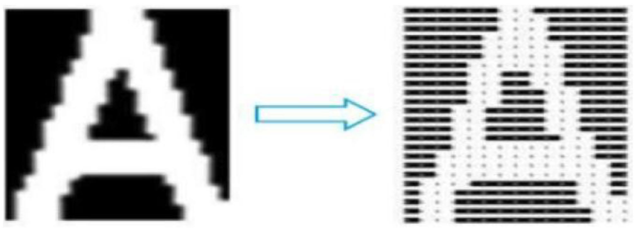

Fig. 7 *Digitisation of image character [81]*

This noise reduction procedure ensures the image for getting rid of this unwanted information.

Owing to forming the input of the recognition process, this normalisation is required in order to resize the isolated characters and for fitting these characters into the binary window. After that, the characters need to be segmented into a block which does not possess any additional white spaces among every side of these characters. After that is the digitisation procedure. In this image digitisation procedure, the individual characters get converted into a binary matrix according to specified dimensions, whereas the similarity of dimensions between the saved patterns from the database and the input gets ensured through this procedure. For an instance, in Fig. 7, the alphabetical character A gets digitised into 360 ($=24 \times 15$) binary matrix, whereas each possesses either white or black coloured pixel [79]. Converting the data into necessary meaningful information is very important. For this reason, a binary function of the image could be implemented, whereas for every white pixels, the binary value 1 (foreground) gets assigned and for every black pixels, the binary value 0 gets assigned as the background as well [80].

The existing methods on recognition of vehicular LP characters are categorised according to the utilised attributes as given below.

4.1 Pattern matching attributes

This pattern matching or template matching procedure is a straightforward and relatively simpler technique in this recognition of vehicular LP characters [24, 60]. This template matching procedure is competent for recognising the vehicular LP characters having non-rotating, fixed size, non-broken, and single-font characteristics. This template matching procedure generates incorrect output in the case of any rotation, noise or font change, and the characters differ from the templates [82]. The measurement of the uniformity between the template and a character gets analysed in this procedure. In spite of being utilised in binary images preferably, this procedure can possess better performance for the grey-scaled images as well if the templates are built properly [36]. A majority of these pattern matching procedures utilise the binary images because if there is any alteration in the illumination situations, the grey-scaled images get changed as well [82]. The pattern matching algorithm because of the recognition of vehicular LP characters has been deployed in [39, 83] as well. A pattern matching procedure has been implemented in [10, 84, 85] after the extracted characters get resized according to an identical size. In the literature, some procedures based on the uniformity measurement have been defined as well. Some of the procedures are based on the Jaccard value [31], the Hamming distance [24], the Bayes decision method [77], and the Mahalanobis distance [86]. In the case of utilising the Mahalanobis distance being the minimum distance classifier, the features of every model have to possess a normal distribution must. Another technique integrated with the Hausdorff distance has been implemented in [84, 87]. Two binary images get compared with each other in this procedure or this Hausdorff distance technique can also be defined as a technique of comparing between the sets of two active pixels. The recognition rate of this procedure is very near to the recognition rate of the neural network classifiers, but this procedure is slightly slower than the neural network classifiers.

4.2 Deploying extracted attributes

All of the pixels from a character do not possess the same significance in order to distinguish the character. As a result, the feature extraction procedure in which some of the character attributes get extracted plays a relatively better role than the template matching technique for the grey-level images [60]. It also requires less processing time than the template matching procedures since all the pixels are not being processed in this technique. For measuring the uniformity, a feature vector gets formed by the extracted features where the pre-stored feature vectors get compared with this feature vector. This attribute can conquer the limitations of the template matching procedures if the extracted features are enough robust in distinguishing the characters in the case of distortion [82]. A recognition procedure based on the feature vector integrated with normalisation of the binary characters has been implemented in [88] where a block sized pixel has been deployed in order to divide the each binary character. Another technique based on this feature vector has been implemented in [60, 89] where the binary character has been projected vertically and horizontally for generating the feature vector. The feature vector is extracted in [89] after quantising the projection into four levels.

4.3 Deploying classifiers

For recognising the segmented characters of the LP images, proficiently classifiers are deployed after extracting the features. Artificial neural networks (ANN) and statistical classifiers have been implemented in recognition procedure.

4.3.1 Artificial neural networks: A single artificial neuron/node itself is capable of performing certain information processing. However, multiple nodes are required to be connected with each

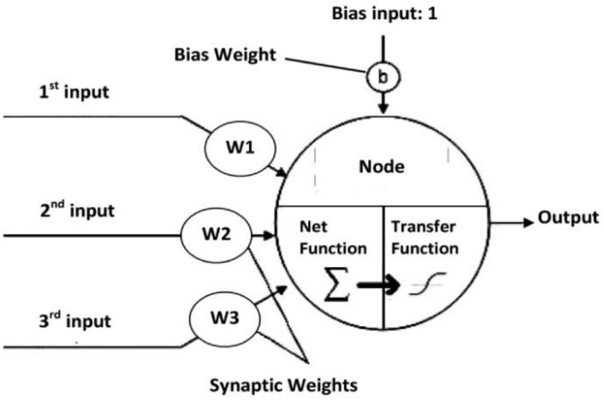

Fig. 8 *Illustration of a node (artificial neuron) in ANN [93]*

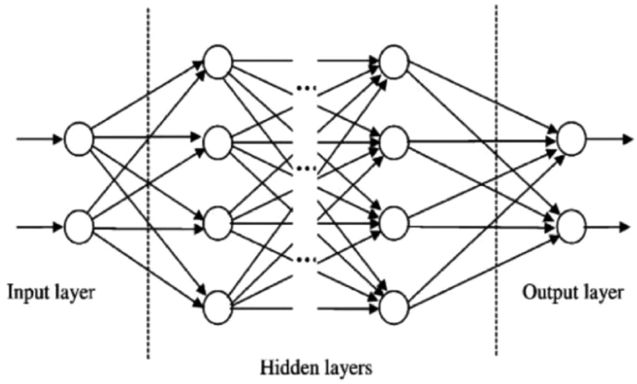

Fig. 9 *Illustration of multi-layer feed-forward neural network [93]*

other in order to form a network of artificial neurons or nodes for performing more powerful computations and complex tasks. Among different architectures of ANN, the multi-layer feed-forward network has been implemented in a number of researches [2, 90, 91] for the identification of the vehicular LP characters. For achieving good performances, the network needs to be trained by several training cycles. After trial and error processing [92], the respective neuron numbers along with the hidden layer numbers need to be defined (see Fig. 8).

A procedure of utilising the three-layered feed-forward ANN integrated with the back-propagation learning algorithm has been implemented in [2] for recognising the segmented characters of the LP images proficiently. Before this, the segmented LP characters had been processed through the thinning procedure for better character recognition system. A total of 600 neurons have been utilised in the input layer and 33 neurons have been utilised in the output layer. For optimal performance, the neuron number in the hidden layer should be two-third of the neuron number of the input layer plus the neuron number in the output layer had been reported. As a result, 300 neurons have been utilised in the hidden layer. A relatively better recognition rate of 96.92% had been reported.

A new algorithm implementing probabilistic neural network (PNN) for the VLPR framework had been introduced in [94], where dual PNN systems had been utilised for recognising the alphabets and the numbers separately. This PNN-based architectures are relatively faster for getting trained and designed because the neurons of the hidden layer gets defined by the training pattern numbers and only once gets trained [95] (see Fig. 9). Another algorithm implementing PNN integrated with column sum vector enumerations has been developed in [96] for recognising the vehicular plates under different illumination situations distance and tilt conditions where a relatively better recognition rate of 96.5% had been reported.

Recently, deep learning architectures (DLA) are being employed for solving computer vision problems. For solving VLPR problems, recurrent neural network (RNN) has been exploited. A long short-term memory (LSTM)-based RNN structure has been implemented in [97] for the character identification in terms of sequence labelling after the LP's sequential features had been extracted by implementing a 37-class CNN. Another RNN model integrated with CNN has been utilised in [98] overcoming the limitations associated with sliding window techniques. The end-to-end training on the labelled LP images is possible in CNN structure, whereas a training data of the pre-segmented characters is required by sliding window approaches. Both of the methods have been reported as segmentation-free and hence capable of avoiding segmentation associated errors.

In the field of machine learning, DLA has emerged as a mainstream topic for the application of VLPR recently. The basic convenience of DLA over traditional existing procedures is the automation of the feature selection system excluding human intervention [99]. A relative comparison of DLA implemented works has been tabulated in Table 4.

4.3.2 Statistical classifiers: After the character segmentation stage, the extracted region of interests are processed under a parameterisation and pre-processing technique before implementing the hidden Markov model (HMM). It had been defined as one of the dual stochastic processes which is observable indirectly (hidden), whereas it can be observed only by some other set of stochastic systems which produce the observed character sequence [106, 107]. Generally, two major approaches are utilised for constructing the HMM for character recognition where one is implemented for every character and another is for every word [106]. The convenience of this procedure is that this technique is capable of learning the differences and the uniformities between the LP image samples. The probabilities or the parameters in the HMM process had been trained by utilising the observation vector that had been extracted from the vehicular LP image samples [108].

Another procedure utilising the HMM integrated with a complex parameterisation and pre-processing technique has been implemented in [109] for recognising the characters of the LP images with a relatively better recognition result of 95.7%. An SVM-based technique integrated with fuzzy logic has been implemented in [110] for the Malaysian LPs. The feature selection, tuning, and training of fuzzy SVM parameters had been performed by implementing a memetic particle swarm optimisation algorithm which has been illustrated in Fig. 10. Another dual-staged hybrid recognition method combined with structural and statistical recognition process for attaining higher recognition rate and robustness has been implemented in [111] where four statistical subclassifiers had been utilised in the recognition process. The system had been applied to a large data set including >10,000 LP images and a better output of 95.41% recognition rate had been reported.

4.4 Discussion

Character recognition stage plays a very significant role in VLPR framework in identifying the numbers of the LPs. However, this recognition stage may suffer from some complications. Sometimes, after the normalisation step, the produced characters may vary from the database samples because of the different shapes, styles, and sizes of the characters which could end in identifying the false characters. This could enhance the complexity of the entire process and affect the performance of the whole framework. This is very significant for any of the processes to differentiate the extracted characters properly because there are some possibilities of the process being confused because of the uniformities among the forms of size and shape. Based on the utilised attributes, the existing character recognition procedures have been classified here in Section 4. The methodology, conveniences, and inconveniences of the each class of attribute have been discussed in a nutshell in Table 5.

5 Future aspects

A wide number of research works on VLPR have been proposed by the researchers in the past several decades and many significant improvements have also been made. However, still there are many

Table 4 Relative comparison of some deep learning methods

Methods	Conveniences	Limitations	Reference	Accuracy, %
DLA integrated with combined CNN and KELM (Kernel-based extreme learning machine)	KELM enabling better results on classification with shorter training period for CNN	computational complexity, implemented on Chinese LPR only, character 'zang' was not recognised for many runs	[100]	96.38
37-class CNN trained method for character detection where LSTM integrated RNN has been implemented for overcoming sequence labelling problem	robust under various conditions, cascaded framework enables CNN for rapid detection. Two different data sets (Caltech cars, AOLP) are utilised	sliding-window-based multi-scaled localisation method is much time-consuming than other related approaches for real-time application	[97]	94.85
an YOLO (you only look once) inspired network integrated with CNN	relatively better segmentation performance and faster processing	non-robust in identifying small objects, utilised only Brazilian 7-character, one row LPs	[101]	93
a DCNN (deep CNN) method integrated with MTL (multi-task learning) learning method for the generalisation of error rate in recognition	robustness for real-time applications. Artificially generated images have been utilised for training model directly	error might occur for broken or mutually joined characters and multi-styled LPs. Only fixed styled Korean LPs utilised for recognition	[102]	98.02
a visual attention-based DLA integrated with two classifiers: CNN-enabling learning and SVM-enabling multi-channel processing	robust performance under noise contamination and illumination variation	only implemented for Chinese LPs, higher processing time, and complexity for double classifiers	[103]	97.2
combined two-stage classifiers: Winnows classifier and CNN for localisation. HMM with probabilistic inference technique integrated with Viterbi algorithm	segmentation-free method that overcomes the limitations from character segmentation, relatively less processing time	computational complexity	[104]	99
an embedded system integrated with CNN for recognition of the characters.	a relatively simpler model implemented with GPU for faster processing	built-in system excluding detection line. Non-robust with illumination variation and broken plates	[105]	95.24

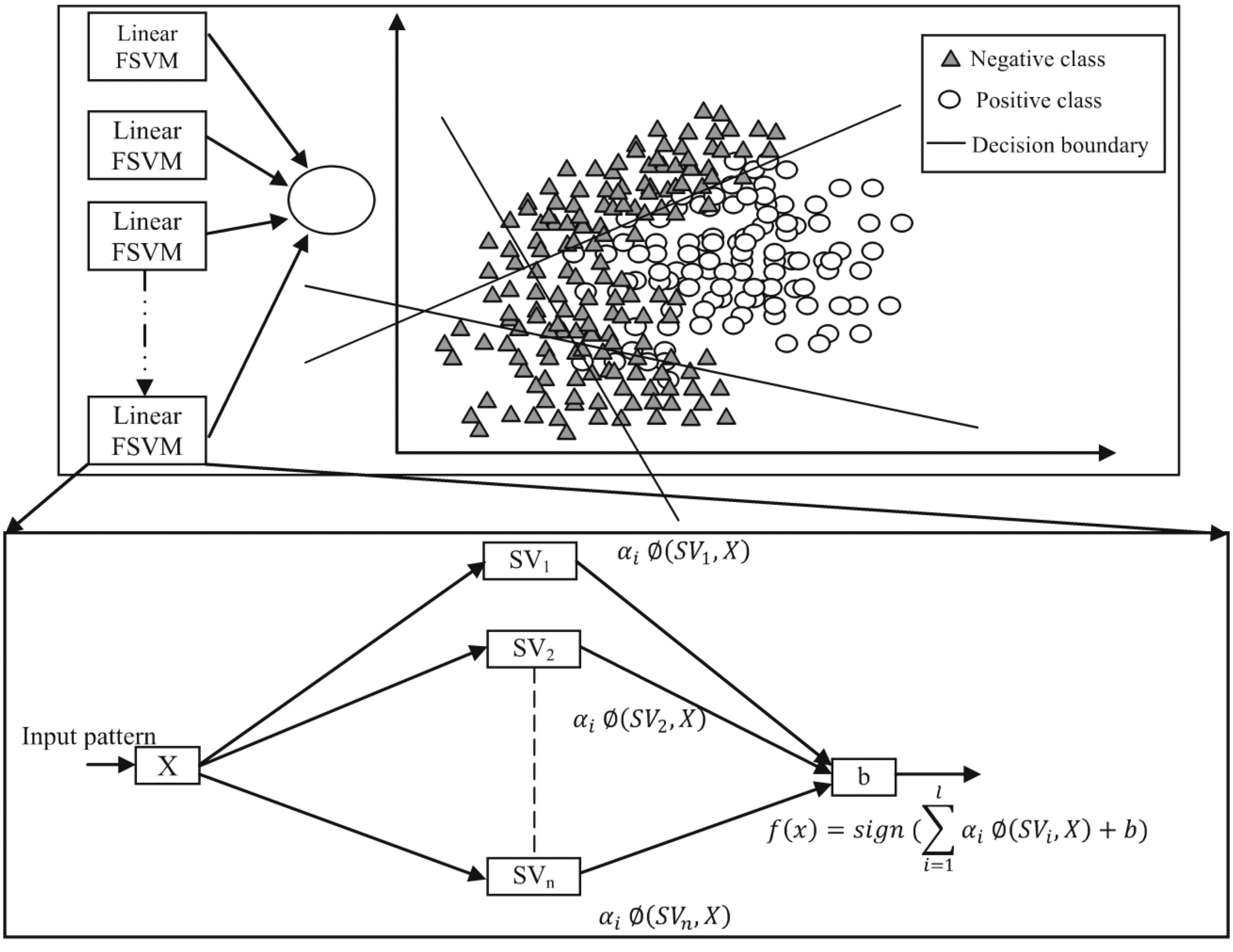

Fig. 10 *Proposed fuzzy SVM in [110]*

Table 5 Relative comparison of the existing recognition methods with respect to the attributes

Class	Conveniences	Inconveniences	Reference	Accuracy
pattern matching attributes	more competent for recognising non-broken, fixed size, single-font characters. Straightforward and relatively simpler technique	higher processing time because of processing inessential pixels, not robust for thickness change, rotation, noise, multi-font, broken characters	[112], [10]	95.7%, 95.6%
extracted attributes	faster recognition, capable of extracting the salient attributes, robust in distinguishing the characters in the case of distortion	recognition performance might get degraded by the non-robust attributes, requires extra time for extracting the attributes	[33], [14]	98.34%, 98.6%
classifiers:				
ANN	relatively simpler implementation, higher	additional processing time for training the network,	[113]	98.5%
	recognition efficiency in the case of huge amount of data.	processing complexity.	[2]	96.92%
statistical classifiers	capable of learning the differences and the uniformities	Relatively complex, higher processing time.	[114]	99.5%
	of the multiple characters		[109]	95.7%

factors that need to be taken into account for designing a robust VLPR system capable of functioning properly under various illumination and environmental situations, different styled plate conditions. In the VLPR system, the multi-styled VLPs possessing various syntax and fonts should be dealt with for more efficiency and robustness. This issue has been taken into account in few existing works, whereas the constraints regarding this issue have not been overcome thoroughly. For overcoming the problems associated with the multi-style number plate, based on four critical parameters, such as the rotation angle of the plate, the utilised alphanumeric character types, the line number of the characters, and the character formats, a procedure has been proposed in [115]. The system has been applied to a large data set including 16,800 images and a relatively better overall success rate of 90% has been reported where a processing speed of 8 f/s has been utilised for the images with lower resolution. Thermal image processing has been implemented in [116] which brings a better result for night-time traffic surveillance. In order to cope with this poor visibility problem which appears in night-time particularly, some supplemental lighting instruments for focusing the visible portions, for example, the tail-light or the head-light, could be implemented additionally with camera [117, 118]. So, vehicular plate recognition during night-time could be a field of interest to the researchers.

Still images or few frames from the image sequence get captured and analysed in most cases of the VLPR system. For improving the system performance significantly, the temporal information of video could be exploited. The implementation of temporal information enhances the efficiency of the recognition stage by tracking vehicles with respect to time for estimating the LP motions. For this reason, a procedure based on the reconstruction of super-resolution has been implemented in [119] where subpixel shifted images, multiple lower resolution images get combined for constructing higher resolution images. Some more issues should be given importance for future research in VLPR system. To cope with the different illumination situations, more robust pre-processing techniques should be implemented for getting better enhancement. Moreover, new sensing techniques can be implemented where the impact of change of illumination is relatively less. Besides, for the video-based VLPR systems, another challenge is the motion detection by extracting the frame of the moving vehicles. Furthermore, there are uniformities among the ambiguous characters. Recognition error may happen for identifying these characters (O/0, I/1, Z/2, C/G, D/O, K/X, A/4, S/5, B/8). These ambiguity issues should be given importance for future research in OCR. To cope with this problem, finding the aspect ratio (horizontal to vertical length) of the character might help. Vehicle recognition from the blurred image is another challenge in this field. On the basis of natural image matting, a vehicular identification procedure has been implemented in [120] for the blurred vehicular LP images. Moreover, the existing VLPR video camera resolutions are generally low. However, in recent applications, cameras utilised in this VLPR system are with high definition where the object details get preserved at a higher distance. The computational costs get increased because of processing a big amount data. An operator context scanning procedure has been introduced in [121] for addressing this issue where the pixel operators have been utilised as a sort of sliding window. The processing speed gets increased by 250% in this procedure than the general SCW techniques.

6 Conclusion

A comprehensive investigation on the existing VLPR techniques has been presented here where an analytical review has been carried throughout this paper on the basis of the utilised attributes and the procedures have been categorised as well. An analytical comparison has also been presented according to each categorised attributes including with conveniences, inconveniences, and recognition results. The commercial VLPR systems have not discussed here because the operational procedures of these commercial systems are confidential stringently and for many promotional aspects, the performance rates get overestimated generally. The VLPR framework on the basis of existing techniques has been focused here by the aspects of detecting, segmenting, and recognising the plates. VLPR-based future forecast including with some potential challenges in this field has been addressed in this paper. Lower luminous night-time plate recognition, lower resolution, and different shaped multi-styled number plate identification, speeding vehicle detection, ambiguous alphanumeric character identification, skewed and blurred plate recognition, vehicle occlusion, and number plate identification under various hazardous situations, i.e. rainy, snowy, should be taken into account for designing a robust VLPR system in future research.

7 References

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