Video–Based License Plate Detection Algorithms

Hossam El-Din Moustafa, Shaima Abdel-Kader, Mohy Eldin A.Abo-Elsoud, Rasheed M.El-Awady

† Mansoura University, Faculty of Engineering, Mansoura ,Egypt

Summary
License plate detection and recognition system (LPDR) is applicable to wide range of uses such as highway toll collection, traffic management, and many more. One of the problems of this application is finding the position of license plate from cars because many cars have difference in uncertain positions of license plates and unclean license plates. The purpose of this paper is to assess the efficiency of simple algorithm, applied to find the position of license plates from a video frame. This research can detect a license plate from the front or the rear of a car. The suggested algorithm allows users to capture the picture from the video file and then to detect the license plate position of that video. The video captured by video camera will appear in the MPEG file format then its converted to avi file format to be suitable for Matlab. The presented algorithms were applied on Egyption car plates. The recognition rate was 96.345%.

Key words:
License plate detection (LPD), license plate segmentation, license plate recognition (LPR), discrete cosine transforms (DCT). Vehicle license plate detection (VLP),motion picture experting group(MPEG).

1. Introduction

With the rapid development of highway and the wide use of vehicle, people start to pay more and more attention on the advanced, efficient and accurate intelligent transportation systems (ITSs). The task of recognizing specific object in an image is one of the most difficult topics in the field of computer vision or digital image processing. Vehicle license plate detection (VLPD) is also very interesting in finding license plate area from vehicle image. The vehicle license plate detection is widely used for detecting speeding cars, security control in restricted areas, unattended parking zone, traffic law enforcement and electronic toll collection. Last few years have seen a continued increase in the need for and use of VLPR. The license plate detection is an important research topic of VLPR system. Because of different conditions such as poor illumination and varied weather, it is important and interesting how to segment license plate fast and perfectly from road images which often contain vehicles.

In this paper an application namely License Plate Recognition (LPR) for recognizing License Plate of real-time moving vehicles is introduced .In Section 1 gives an introduction. Section 2 presents the data set used in the present work.Section3 introduces a theoretical background about previously used techniques for LPR.In Section 4, the difficulties of these techniques are discussed. Section 5 presents video compression which used based on Simulink. In Section 6 first algorithm applied on frame of compressed video, based on Hough transform is introduced. In section 7 present another technique based on vertical edge detection after cropping the frame. The last Section presents a third modification algorithm based on Simulink . A comparison between the three algorithms is also included in Section 9.

2. Data Sets

Video data source in developing and testing LPD algorithms. The video data in datasets is captured using digital video cameras mounted on top of street lamp poles overlooking stop signs. Figure 1 shows a typical frame captured from camera. The video stream has a resolution of 640 × 480 and sampling is done at 25 frames per second.

Fig. 1 Original Video

3. Theoretical Background

This section provides a descriptive summary of some methods that have been implemented and tested for VLPD. As far as detection of the plate region is concerned, researchers have found many methods of locating license plate.For example, a method based on image segmentation technique named as sliding windows (SW) was also

Manuscript received November 5, 2011
Manuscript revised November 20, 2011

proposed for detecting candidate region (LP region) [1], main thought of image segmentation technique in LP can be viewed as irregularities in the texture of the Image and abrupt changes in the local characteristics of the image, manifesting probably the presence of a LP. A Conventional statistical classifier based on the k nearest Neighbors' rule is used to classify every pixel of a test image to obtain a pixel map where group of positive samples probably indicates the location of a license plate. In this system, time exhausting texture analysis is presented in [2], where a combination of a “kd-tree” data structure and an “approximate nearest neighbor” was espoused. The computational resource demand of this segmentation technique was the main drawback, taking an average of 34 seconds in processing of single image. In [3], the pulse coupled neural network (PCNN) is proposed and implemented for LP identification.

Fuzzy logic has been applied in detecting license plates. Authors made some intuitive rules to describe the license plates and gave some membership functions for fuzzy sets e.g. “bright,” “dark,” “bright and dark sequence,” “texture,” “yellowness” to get the horizontal and vertical plate positions [4]. Prior knowledge of LP and color collocation is used to locate the license plate in the image [6] as part of the procedure of location and segmentation. Hough Transform (HT) for line detection was proposed on the assumption that the shape of license plate is defined by lines in [7]. A modified color texture-based method for detecting license plate in images was presented in [8]. A support vector machine (SVM) was used to analyze the color and texture properties of LPs and to locate their bounding boxes applied by a continuous adaptive mean shift algorithm (CAMShift). The combination of CAMShift and SVMs produces efficient LP detection as time-consuming

color texture analysis for less relevant pixels is restricted, Leaving only a small part of the input image to be analyzed.

In addition, finding candidate areas by using gradient information, it is verified whether it contains the plate area by introducing a template of the LP in [9]. A region-based License plate detection method was presented in [10], which firstly applies a mean shift procedure in spatial range domain to segment a color vehicle image in order to get candidate regions. Other approaches for segmentation of vehicle plates such as edge image improvement to detect a number of car plates in [11] and an approach using mathematical morphology method to detect license plate area [12] were also proposed.

Currently, some researchers prefer a hybrid detection algorithm, where license plate location method based on corner detection, edge detection, characteristics of license shape, character’s connection and projection is presented in [15, 17] and [16] is another method which is based on the color collocation of the plate’s background and characters combined with the plate’s structure and texture to locate the VLP. Image enhancement and Sobel operator to extract out vertical edges and finally search plate region by a rectangular window was presented in [17].

4. Difficulties

There is a number of possible difficulties that the software must be able to cope with. These include:

(a) Poor image resolution, usually because the plate is too far away but sometimes resulting from the use of a low-quality camera.

(b) Blurry images, particularly motion blur. Poor lighting and low contrast due to overexposure, reflection or shadows.

(c) An object obscuring (part of) the plate, quite often a tow bar, or dirt on the plate. (d)A different font, popular for vanity plates (some countries do not allow such plates, eliminating the problem).

(e) Circumvention techniques.

(f) Lack of coordination between countries or states. Two cars from different countries or states can have the same number but different design of the plate.

While some of these problems can be corrected within the software, it is primarily left to the hardware side of the system to work out solutions to these difficulties. Increasing the height of the camera may avoid problems with objects (such as other vehicles) obscuring the plate but introduces and increases other problems, such as the adjusting for the increased skew of the plate.

On some cars, two bars may obscure one or two characters of the license plate [18]. Bikes on bike racks can also obscure the number plate, though in some countries and jurisdictions, such as Victoria, Australia, "bike plates" are supposed to be fitted. Some small-scale systems allow for some errors in the license plate. When used for giving specific vehicles access to a barricaded area, the decision may be made to have an acceptable error rate of one character. This is because the likelihood of an unauthorized car having such a similar license plate is seen as quite small. However, this level of inaccuracy would not be acceptable in most applications of an ANPR system.

5. The Compression Technique

The present section introduces the basic video compression process which will be the first step of all LPDR algorithms. In the next sections, three video-based algorithms will be explained, then applied to the Egyptian license plate recognition.

5.1 Video Compression

Figure 2 illustrates video compression using motion compensation and discrete cosine transform (DCT).It calculates motion vectors between successive frames and uses them to reduce redundant information. Then it divides each frame into submatrices and applies the discrete cosine transform to each submatrix. Finally, it applies a quantization technique to achieve further compression. The Decoder subsystem performs the inverse process to recover the original video.

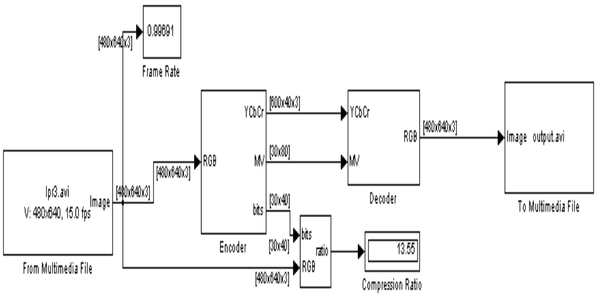

Fig.2 the Video Compression Model

4.1.1Encoder Subsystem

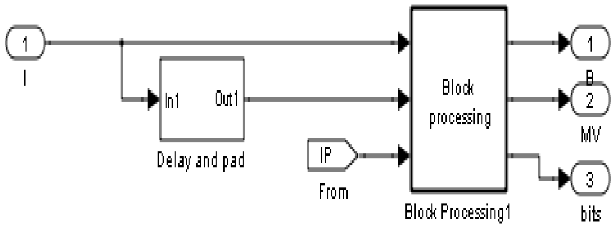

Fig.3 Encoder Subsystem

The Block Processing block sends 16-by-16 submatrices of each video frame to the Block Processing block's subsystem for processing. Within this subsystem, the model applies a motion compensation technique and the DCT to the video stream. By discarding many high-frequency coefficients in the DCT output, the algorithm reduces the bit rate of the input video shown in figure 3.

5.1.2Video Compression Results

The Decoded window shows the compressed video stream. Figure 4 shows the compressed video frame which still contains the most important features.

Fig.4 Video after Compression

6. The First Proposed Technique

The first technique uses the region of interest (ROI) containing the license is obtained using the following steps:

i. image enhancement
ii. Edge detection and Hough transform

6.1 Image Enhancement

Fig 5 wiener filter output

The wiener filter is used to convert the input image in fig 4 which is a frame of compressed video to desired output image in the best way as possible. The approach of reducing degradation at a time allows us to develop a restoration algorithm for each type of degradation and simply combine them .The wiener filtering executes an optimal tradeoff between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously. The wiener filtering is optimal in terms of the mean square error as seen in fig.5.

6.2 Edge Detection and Hough Transform

The algorithm depends on estimating the position of the license plate region within the scene image in order to reduce the search space before applying any technique .An extremely noticeable characteristic of license plates is their rectangular shape. This set of experiments takes this important feature into account and makes use of edge detection and the Hough transform to detect horizontal and vertical lines that could be responsible for license plate borders in a scene image. In order to detect the borders or edges in an image it is useful to focus on abrupt changes in intensity in local neighborhoods. Enhancing the edges will help to bring the license plate borders forward. The 3×3 vertical and horizontal Sobel operators (masks) were convolved with the scene image in fig1. In order to combine the vertical and horizontal edge response, the magnitude of the gradient is computed to generate an edge. Figure 6 shows Sobel edge detection on care image.
Identifying the edges in the scene image is the first step to locate the license plate borders. It is important to identify the edge pixels that form lines that could be responsible for such borders. The Hough transform is a technique for detecting lines or curves in a picture by applying a coordinate transformation, such that all the points belonging to a curve of a given type map into a single location in the transformed space. The transformed space is quantized into an accumulator array for representation, and for each pixel of interest, votes are added to the array locations associated to the transformed coordinates matching.

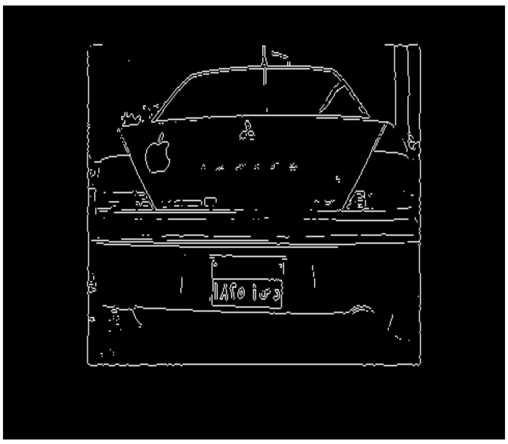

Fig .6 Sobel edge detection on the car image

Hough transform on list of border pixels gives a line equation, which describes top or bottom border. It enables to find a plate height by finding a distance between two lines.
The Hough array is defined for Θ in the[0,170]° range ,with one –degree increments for each bin. The range for ρ is determined by computing the diagonal length of image. All applicable location of Θ and ρ in Hough transform are incremented by one. The resulting Hough array is shown in figure 7.
There is a common side effect of the Hough transform approach, known as phantom lines. In this problem the mainly important is the horizontal and vertical lines caused by the license plate borders in the image. Therefore, speed up the approach by only considering values for θ that correspond to close approximations of horizontal and vertical lines, within a one to two degree margin.

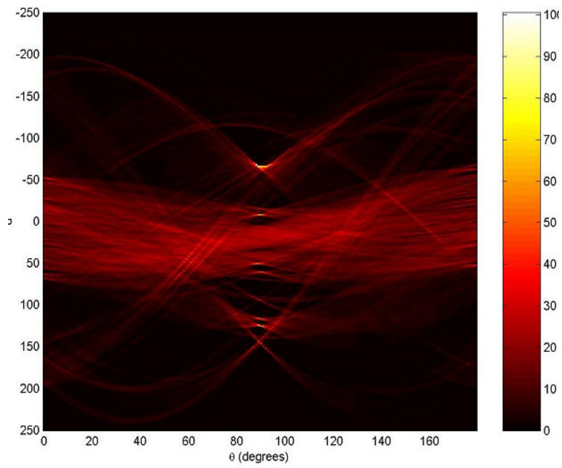

Fig.7 Hough array

The elimination of phantom lines is achieved by running the Hough transform on the original image, finding the maximum accumulator array location and eliminating the edge points in the image that match the line defined by the corresponding values of θ and ρ. The Hough transform is run again to generate a new Hough array and the process is repeated until an acceptable amount of lines or a minimum threshold for the accumulator array values is reached. During the elimination of phantom lines, the procedure ensures that a few vertical lines are preserved, as these usually have a lower bin count than the horizontal ones and tend to disappear from consideration otherwise. Figure 8 shows the result of phantom line removal. Aspect ratio and approximate size can aid in isolating rectangles formed by the line crossings. Once the line crossings are detected, they are considered as possible rectangle corners. Each corner point is paired up with all other corner points in the image that are to its right and below it. Then the gradient of the line that crosses each pair of points is computed in order to determine if the pair of corners may belong to a 2:1 rectangle (a gradient approximately equal to -0.5 is expected). The identified rectangles are depicted by their diagonals in Fig 8. The borders of each candidate rectangle are followed, with a ±1 pixel margin, to determine if the image edges are present under the hypothetical rectangle. The rectangle with the maximum response is singled out as the license plate region .While further modifications to the Hough transform procedure may help to increase accuracy, other techniques may exploit the textural qualities in the license plates in order to facilitate plate detection. Figure 9 show the license plate.

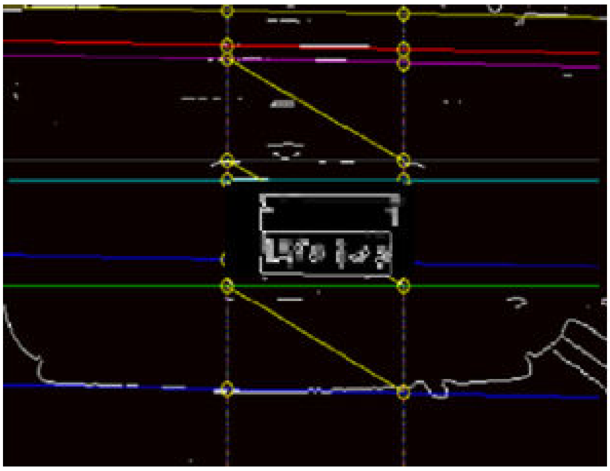

Fig 8 Line crossing(candidate corner) detection

Unfortunately, this technique is not applicable to the problem instances where the license plate borders do not produce high enough luminance changes to be detected as edges (e.g. white background license plates on white vehicles). In image set the approach only achieved a 90% recognition rate in detection and extraction. Furthermore, after several optimization modifications, the processing time was approximately 1.6 second in the test computer.

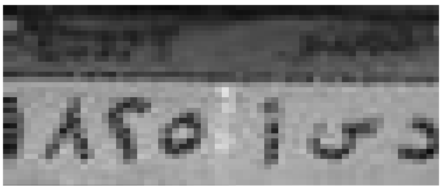

Fig.9 final output

7. The second proposed Technique:

The second Proposed technique is based on the following steps :

(i) Histogram equalization

(ii) Image segmentation and removal of border and background

(iii) Vertical Edge Matching

(iv) Black to White Ratio and Plate Extraction

7.1. Histogram Equalization

Histogram equalization is an image transformation that computes a histogram of every intensity level in a given image and stretches it to obtain a more sparse range of intensities. This manipulation yields an image with higher contrast than the original. The process is based on the creation of a transfer function that maps the old intensity values to new intensity values.
For instance, let T be the transfer function, 'T (34) = 44' denotes that each pixel value of 34 present in the image will be replaced by a 44. The transfer function is based on the computed probabilities of each intensity value appearing on the image. This has the end effect of spreading out the most commonly appearing pixel intensities to cover a larger range. The following images demonstrate the effect of histogram equalization on sample input images.

Fig.10 A frame after histogram equalization

To increase the contrast of the gray scale image from the PC, histogram equalization is used. As shown in Figure 10, the histogram equalized image has much better contrast, especially around the license plate region, than the original image.

7.2 Removal of Border and Background

Fig. 11 Cropping image

Often the license plate will be in the lower half of the upper half of the image will be removed .The new image will be about 1/3 original image so the recognition algorithm will be very fast. The cropped image is shown in Fig. 11.

The proposed technique uses the Sobel edge detector because it shows better results. The threshold used by the edge detector is dynamic because the system takes an automatic value from the algorithm. The Sobel edge detector uses a 3×3 mask, which is applied on the cropping image to give the resultant edged image. The edge detection algorithm is not time consuming. First of all, get the vertical edges using Sobel edge detection function for the both sides of the image and then removes the area outside tall vertical edge as shown in Fig. 12.

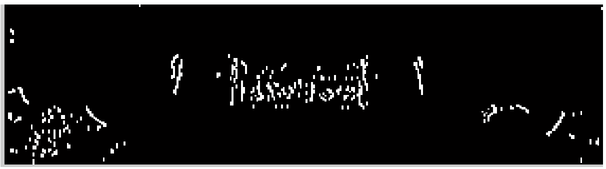

Fig.12 Sobel edges

7.3 Vertical Edge Matching

In this phase, the width to height ratio of the license plate is used to match the vertical edges for finding the region of where there is a probability of a license plate. The ratio of width to height of Egyptian license plates is about 2:1. After the filtering step, the image in fig 12 is extracted, having several vertical regions. Only two of the regions could be the possible boundary of the license plate. The task of vertical edge matching is to find out the correct pair of regions that include the license plate. To achieve this task, the width to height ratio of the rectangular area between two vertical regions is compared with the actual standard ratio of a license plate. The standard ratio is taken between 1.75 : 1 to 2.25 : 1. Figure 13 shows the extracted license plate for the matched vertical edges.

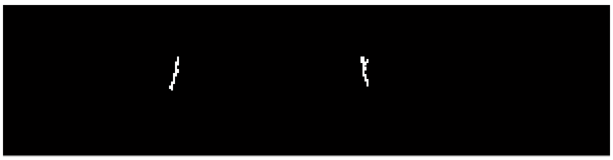

Fig.13 Image after removing small elements

Figure 14 explains how the vertical edge matching algorithm computes the horizontal and vertical distances between two regions. In the figure, Region 1 and Region 2 are processed for the possibility that they form two vertical edges of a license plate. The width to height ratio of Region 1 and Region 2 certainly does not match with the specified ratio (i.e. between 1.75:1 to 2.25:1), so this pair

Cannot be the region of interest. In Figure15, Region 2 and Region 3 are the possible pair of vertical edges of the license plate.

In some cases, there is a possibility of more than one pair of regions that satisfy the above threshold and there are three regions satisfying the constraint of width to height ratio. To overcome this problem, the black to white ratio of these regions is taken, to get the probable license plate. Figure 15 shown the final output.

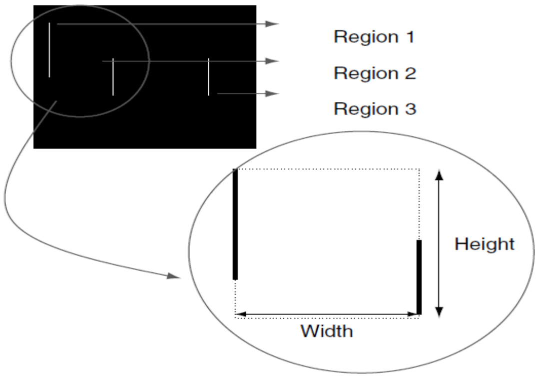

Fig. 14 Computation of horizontal and vertical distances between two extracted regions

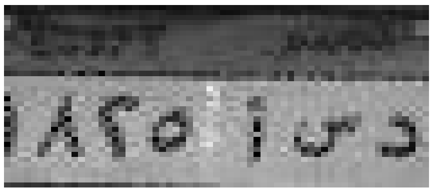

Fig.15final output

7.4 Black to White Ratio and Plate Extraction

This phase is considered when more than one pair of probable license plate regions are obtained after the matching of vertical regions for their width to height. All the coordinate points for every pair of matched regions are stored and the black to white ratios of the stored regions are calculated Since the characters on the license plate contain white pixels, so the B/W ratio for the probable plate region is much less than the ratio of any of the extracted regions which do not contain a license plate. Therefore, if the pair is a possible license plate, then the ratio is within a specified threshold. The threshold is selected based on tests performed on a number of plates.

8. The third Proposed Technique

The third technique uses dimensional frequency domain cross correlation, this procedure includes the: (a) Gaussian pyramid, (b) Two Dimensional Fast Fourier Transform.(c) Normalized 2D Cross- Correlation**.**

The algorithm shows usage of Video and Image Processing System objects to find a license plate in a video and track it. The algorithm is based on normalized frequency domain cross correlation between the target and the image under test. The video player window displays the input video with the identified target locations. Also it displays the normalized correlation between the target and the image which is used as a metric to match the target. Figure16 shows the Simulink model used for license plate detection

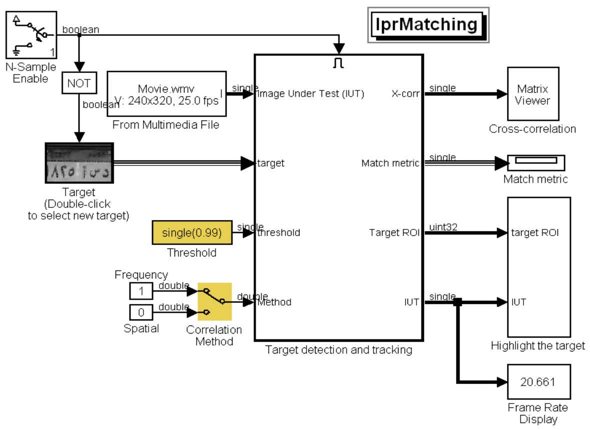

Fig..16 LPR Detection Model

The algorithm consists of the following steps:

(i)Select the target image from the GUI (license plate) and also provide the number of similar targets to be tracked

(ii)Down sample the target image by a predefined factor using the Gaussian pyramid system object. You do this to reduce the amount of computation for cross correlation.

(iii)Rotate the target image by 180 degrees, and perform zero padding so that the dimensions of both the target and the input image are the same.

(iv)Compute the 2-D FFT of the target image

(v) Create a system object to calculate the local maximum value for the normalized cross correlation.

8.1Gaussian pyramid

Gaussian pyramid is a technique used in image processing, especially in texture synthesis. The technique involves creating a series of images which are weighted down using a Gaussian average (Gaussian blur) and scaled down. When this technique is used multiple times, it creates a stack of successively smaller images, with each pixel containing a local average that corresponds to a pixel neighborhood on a lower level of the pyramid significant speedup can be achieved by the usage of so-called image pyramids. The bottom level 0 of the pyramid consists of the original image whereas the higher levels are built by sub sampling or averaging the intensity values of adjacent pixels of the level below. Therefore at each level the image size is reduced .Correlation initially takes place in a high level of the pyramid generating some hypotheses about coarse object locations. Due to the reduced size this is much faster than at level 0. These hypotheses are verified in lower levels. Based on the verification they can be rejected or refined. Eventually accurate matching results are available. During verification only a small neighborhood around the coarse position estimate has to be examined. This proceeding results in increased speed but comparable accuracy compared to the standard scheme. The main advantage of such a technique is that considerable parts of the image can be sorted out very quickly at high levels and need not to be processed at lower time .

8.2 Two Dimensional Fast Fourier Transform

Fourier Transformation (FT) is probably the most popular transform being used (especially in electrical engineering and signal processing), There are many other transforms that are used quite often by engineers and mathematicians.

Every transformation technique has its own area of application, with advantages and disadvantages the process of obtaining the spectrum of frequencies H(f) comprising a time-dependent signal h(t) is called Fourier Analysis and it is realized by the so-called Fourier Transform (FT). In most cases. This form of image representation is known as the time domain spectrum. However, in order to filter the signal, it has to be converted into the frequency domain.It breaks down a signal into constituent sinusoids of different frequencies.

The Cooley–Tukey algorithm [19], named after J.W. Cooley and John Tukey, is the most common fast Fourier transform (FFT) algorithm. It re-expresses the discrete Fourier transform (DFT) of an arbitrary composite size N = N1N2 in terms of smaller DFTs of sizes N1 and N2, recursively, in order to reduce the computation time to O(N log N) for highly-composite N (smooth numbers). Because of the algorithm's importance, specific variants and implementation styles have become known by their own names.

More generally Cooley–Tukey algorithms recursively re-express a DFT of a composite size N = N1N2 as:

(i)Perform N1 DFTs of size N2.

(ii)Multiply by complex roots of unity called twiddle factors.

(iii)Perform N2 DFTs of size N1.

The equation of the two-Dimension Fourier transform is shown below:

$$X_{N_2 k_1 + k_2} = \sum_{n1=0}^{N_1-1} \sum_{n2=0}^{N_2-1} x_{N_1 n_2 + n_1} e^{-\frac{2\pi i}{N_1 N_2}(N_1 n_2 + n_1)(N_2 k_1 + k_2)} \quad (1)$$

Where each inner sum is a DFT of size N2, each outer sum is a DFT of size N1, and the [...] bracketed term is the twiddle factor.

8.3 Normalized 2D Cross- Correlation

In signal processing, cross-correlation is a measure of similarity of two waveforms as a function of a time-lag applied to one of them. This is also known as a sliding dot product or inner-product. It is commonly used to search a long duration signal for a shorter, known feature. It also has applications in pattern recognition, single particle analysis, electron tomography averaging, cryptanalysis, and neurophysiology.
Normalized 2D cross correlation uses the following general procedure:
(i)Calculate cross-correlation in the spatial or the frequency domain, depending on size of images. (ii)Calculate local sums by pre-computing running sums
(iii)Use local sums to normalize the cross-correlation to get correlation coefficients.
The implementation closely follows following formula from:

$$\gamma(u,v) = \frac{\Sigma_{x,y}\left[f(x,y) - \overline{f}_{u,v}\right]\left[t(x-u,y-v) - \bar{t}\right]}{\left\{\Sigma_{x,y}\left[f(x,y) - \overline{f}_{u,v}\right]^2 \Sigma_{x,y}\left[t(x-u,y-v) - \bar{t}\right]^2\right\}^{0.5}} \quad (2)$$

Where:
f is the image.
$\bar{t}$ is the mean of the template

$\overline{f}_{u,v}$ Is the mean of $f(x,y)$ in the region under the template.

Perhaps the most straight forward approach to plate recognition is 2D cross correlation of a scene image with a prototype representation of the object to be found. Here, the model consists of a so-called template image, which is a prototype representation of the gray value appearance of the object. Model generation is done in a training phase prior to the recognition process. For example, the template image is set to a reference image of the object to be found. 2D correlation is a example of an appearance-based scheme, as the model exclusively depends on the (intensity) appearance of the area covered by the "prototype object" in the training image.
The recognition task is then to find the accurate position of the plate in a video as well as to decide whether the frame contains an instance of the model at all. This can be achieved with the help of evaluating a 2D cross correlation function: the template is moved pixel by pixel to every possible position in the scene image and a normalized cross correlation (NCC) coefficient γ representing the degree of similarity between image intensities is calculated at each position.
High-positive values of γ indicate that the scene image and template are very similar, a value of 0 that indicate no matching.
As a result of the correlation process a 2D function is available. Every local maximum of this matching function indicates a possible occurrence of the object ,If the value of the maximum exceeds a certain threshold value plate is found. Its position is defined by the position of the maximum.
There, a template showing in fig 17 (in green, part) is shifted over a video. At each position, the value of the cross-correlation coefficient is calculated and these values are collected in a 2D matching function indicate high .The start position is the upper left corner; the template is first shifted from left to right, then one line down, then from left to right again, and so on until the bottom right image corner is reached.
This simple method has the advantage to be straightforward and therefore easy to implement. Additionally it is generic, i.e., the same procedure can be applied to any implement. Additionally it is generic, i.e., the same procedure can be applied to any kind of object (at least in principle); there exist no restrictions about the appearance of the object.
Unfortunately, there are several drawbacks. First, the correlation coefficient decreases significantly when the object contained in the scene image is a rotated or scaled version of the model, i.e., the method is not invariant to rotation and scale. Second, the method is only robust with respect to linear illumination changes: The denominator of Equation (2) is a normalization term making γ insensitive to linear scaling of contrast; brightness offsets are dealt with by subtracting the mean image intensity. However, often nonlinear illumination changes occur such as a change of illumination direction or saturation of the intensity values. Additionally, the method is sensitive to clutter and occlusion: as only one global similarity value is calculated, it is very difficult to distinguish if low maxima values of γ originate from a mismatch because the searched object is not present in the scene image (but perhaps a fairly similar object) or from variations caused by nonlinear illumination changes, occlusion, and so on.
To put it in other words, cross correlation does not have much discriminative power, i.e., the difference between the values of γ at valid object positions and some mismatch positions tends to be rather small
Figure 17 show the final output after applying normalized cross correlation for license plate detection.

Fig.17 Final Output

9. Conclusion

Using Hough transform for license plate detection take along time and this technique is not applicable to the problem instances where the license plate borders do not produce high enough luminance changes to be detected as edges (e.g. white background license plates on white vehicles). In frame of compressed video the approach only achieved a 90% recognition rate. By cropping the image and take vertical edge detection then use vertical matching and use black to white ratio. It is not accurate because many License plates come in different sizes and in different Width-Height ratios, different color, the fonts used for digits on license plates are not the same for all license plates.Using this second algorithm its faster then using Hough transform on all image,but its give 90% recognition rate. These problems, and the changing weather conditions, are what make the field of License Plate Recognition a good candidate for testing Pattern Recognition techniques By using Simulink with accuracy about 96.345%.
An LPD system that is used in Real-time, Works well with inexpensive cameras, and do not require infrared lighting or sensors as are normally used in commercial LPR systems. There no database for Egyptian license plate. Simulink which use Two dimension cross correlation in frequency domain proves that it is good technique for license plate detection, it gives an accuracy about 96.345% recognition rate for small data set.

References

[1] C. Anagnostopoulos, I. Anagnostopoulos, V. Loumos and E. Kayafas, “A License Plate-Recognition Algorithm for Intelligent Transportation System Applications,” IEEE Transactions on Intelligent Transportation Systems, vol. 7, No. 3, pp. 377-392, September 2006.
[2] J. Cano and J.-C. Perez-Cortes, “Vehicle License Plate Segmentation in Natural Images,” In Lecture Notes on Computer Science, vol. 2652, F.J. Perales et al., Eds. New york: Springer-Verlag, pp. 142-149, 2003.
[3] M. I. Chacon and A. Zimmerman, “License Plate Location Based on a Dynamic PCNN Scheme,” In: proc. of the Int. Joint Conf. Neural Network, vol. 2, pp. 1195-1200, 2003.
[4] S. -L. Chang, L. -S. Chen, Y. -C. Chung and S. -W. Chen, “Automatic License Plate Recognition,” IEEE Transactions on Intelligent Transportation Systems, vol. 5, No. 1, pp. 42-53, March, 2004.
[5] K. Deb, H. -U. Chae and K. -H. Jo, “Parallelogram and Histogram based Vehicle License Plate Detection,” In: proc. of the IEEE ICSMA, pp. 349-353, 2008.
[6] Q. Gao, X. Wang and G. Xie, “License Plate Recognition Based on Prior Knowledge,” In: Proc. of the IEEE Int. Conf. on Automation and Logistics, pp. 2964-2968, 2007.
[7] V. Kamat and S. Ganesan, “An Efficient Implementation of the Hough Transform for Detecting Vehicle License Plates using DSP’S,” In: proc. of the IEEE Int. Conf. on. RTAS, pp. 58-59, 1995.
[8] K. -I. Kim, K. Jung and J. -H. Kim, “Color Texture- Based Object detection: An application to License Plate Localization,” In Lecture Notes on Computer Science, vol. 2388, S.-W. Lee and A. Verri, Eds. New york: Springer-Verlag, pp. 293-309, 2002.
[9] S. Kim, D. Kim, Y. Ryu and G. Kim, “A Robust License-Plate Extraction Method under Complex Image Conditions,” In: proc. of the IEEE Int. Conf. on ICPR, vol. 3, pp. 216-219, 2002.
[10] W. Jia, H. Zhang, X. He, “Region-based License Plate Detection,” Journal of Network and comp [11] G. H. Ming, A. L. Harvey, and P. Danelutti, “Car Number Plate Detection with Edge Image Improvement,” In: proc.
[11] of the Int. Symp. on Signal Processing and its Applications, vol. 2, pp. 597-600, 1996.
[12] F. Martin, M. Garcia, J. L. Alba, “New Methods for Automatic Reading of VLP’s (Vehicle License Plates),” In: proc. of the IASTED Int. Conf. on. SPPRA, 2002.
[13] L. G. Shapiro and G. C. Stockman, Computer Vision, Prentice-Hall, New Jersey, pp. 56-59, 2001.
[14] S. E. Umbaugh, Computer Imaging: Digital Image Analysis and processing, CRC Press, Florida, pp. 45-50, 93-100, 168-177, 264, 2005.
[15] Z. Xu and H. Zhu, “An Efficient Method of Locating Vehicle License Plate,” In: proc. of the IEEE ICNC, pp.180-183, 2007.
[16] Y. -Q. Yang, J. Bai, R. -L. Tian and N. Liu, “Research of Vehicle License Plate Location Algorithm Based on Color Features and Plate Processions,” In Lecture Notes on Computer Science, vol. 3930, D. S. Yeung et al., Eds. New york: Springer-Verlag, pp. 1077-1085, 2006.
[17] C. Zhang, G. Sun, D. Chen, T. Zhao, “A Rapid Locating Method of Vehicle License Plate based on Characteristics of Characters Connection and Projection,” In: proc. of the IEEE Conf. on Industrial and Applications, pp. 2546-2549, 2007.
[18] M.I.Khalil,Egyption Atomic Energy Authority,Nuclear Research , “ Car Plate Recognation Using the Template Matching Method”In October,2010,International Journal of Computer Theory and Engineering .
[19] L.Auslander,J.R.Johnson,anR.W.Johnson, Multidimensional Cooley- Tukey algorithms revisited, Adv. in Appl. Math. 17 (1996), no. 4, 477519.