Recognition System for Libyan Vehicle License Plate

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Automatic license plate recognition system plays an essential role in real life applications, especially those related to security and traffic managements. It essentially extracts and recognizes number plate information from videos or captured images of the targeted vehicle. Vehicle license plates differ from one country to another and because of this the effectiveness of implementing any particular method or system varies based on the plate type. In this study, we present an automatic detection, segmentation and recognition system for Libyan vehicle license plates. The main challenge in this work is our determination to use images of real vehicle plates in Libya, and the majority of these plates are not in a good condition because of poor vehicle maintenance. Three different approaches were used in the proposed system as follows: (1) Projection histogram based approach is used to locate the authorized plate license; (2) Connected component analysis based approach is used to segment the plate characters; (3) The template matching based approach is used to recognise the extracted characters. The proposed system was tested on 200 vehicle images varying in illumination conditions and backgrounds. The detection accuracy of the implemented system was 87%, the segmentation accuracy was 90% and the recognition accuracy was 86%.

CCS CONCEPTS • Computing methodologies • Artificial intelligence • Computer vision • Computer vision problems • Object recognition

Additional Keywords and Phrases: LPR localisation; LPR segmentation; LPR recognition

1 INTRODUCTION

In the last two decades, the number of vehicles has rapidly increased which causes major problems in security and traffic managements. In particular the process of monitoring vehicles and identifying their owners manually has become almost impossible. This has encouraged the researchers to develop an automatic system to identify the vehicle License Plates (LP) as solutions for such traffic problems.

In 1976, the police scientific development of the United Kingdom revealed the first Automatic License Plate Recognition (ALPR) [1] system. This system has shown a great success in identifying vehicle license plates which was able to retrieve more information on the vehicles and their owners.

During the last 10 years, the number of crimes involving vehicles has been increasing, as well as suicide attacks that target the government institution buildings. Consequently, the necessity of developing the ALPR system in Libya has been increased. To the best of our knowledge, there are very few studies conducted to build such a system for Libyan license plates (e.g. [2]). Therefore, this study can work as a base for future improvements to build automatic license plate recognition system for Libyan plates.

The aim of this study is to implement three selected techniques to test their performance on the Libyan licence plates. These techniques are presented in the literature which are the projection histogram technique to locate the LP [3], the connected component analysis technique to segment the LP's characters [4] and the template matching technique to recognise the LP's characters [4] [5]. The key contributions of the paper are twofold: (1) To the best of our knowledge, this is the first independent study in Libya attempted to build a complete automatic license plate recognition system for Libyan plates; (2) This empirical study provided us with valuable insight about the practical applications of the proposed system, specifically the capability to recognize images of real vehicle plates in Libya (the majority of these plates are not in a good condition because of poor vehicle maintenance).

Recently in Libya, there are two different sizes of the plates for private cars as shown in Figure 1. They both have the same contents which are an authorised license number and one Arabic word (i.e. ليبيا). In this work three popular techniques in the image processing research area (i.e. projection histogram, connected components analysis and template matching with correlation procedure) are used to develop the License Plate Recognition (LPR) system for Libyan license plates. The proposed system is tested on 200 true colour images to investigate its efficiency in detecting, segmenting and recognizing the targeted license plate.

Figure 1: Libyan car license plate types

2 BACKGROUND

A basic LPR system is generally divided into three main stages which are license plate localisation, license plate segmentation and license plate recognition. The success of the LPR system mainly depends on the accuracy output of the localisation process in detecting the license plate from the captured image, the segmentation process in separating the LP characters and the recognition process in recognising the extracted characters.

Although a variety of methodologies have been proposed for constructing an effective LPR system, their performance in detecting, segmenting and recognizing remains a challenging topic [6]. This is attributable to different factors regarding the captured image of the vehicle plate such as poor illumination conditions and mobility of the vehicle. Language and font type used in the plate are also factors affecting the performance of the LPR system [7].

2.1 LP Localization

This stage concerns the problem of extracting the plate from the input image. It is subject to numerous obstacles which related to the plate variation in terms of shape, size, orientation, etc. There have been a large number of localisation techniques reported in the literature such as:

2.1.1 Colour-based method

This method works on extracting the license plate based on its colour. This algorithm is robust to a limited range of the plate colours. In addition, its results are sensitive to different environments such as plate rotation and non-uniform illumination [8][9].

2.1.2 Edge-based method:

This technique primarily considered the simplest localisation techniques. It basically detects license plate region in the captured image using edge density [10].Vertical edges are identified in particular because of their uniform presence in the license plate. This process provides reliable results and does not require heavy calculations as it is performed using the Sobel operator [11].

2.1.3 Morphology method

Another powerful approach in localising the license plate is called mathematical morphology. This approach is well known in the field of image processing for extracting particular regions in the image. The extraction process here is performed based on the characteristics of the desired image region such as boundaries, size and area, shape. The mathematical morphology is a reasonably robust technique which does not require expensive computations [12][13][14].

2.1.4 Histogram method

Histogram is another essential approach in locating the license plate in a grey scale image. It relies on constructing a graph indicating how many of each grey intensity occurs in the targeted image [15]. By manipulating this concept around and calculating the difference between grey intensity instead of counting them, a projection histogram is achieved which is one of the efficient tools in object localisation as will be discussed in Section 3.2.1.

2.2 LP Segmentation

This stage concerns separating plate characters from each other. Partial character connectivity in the used plate language is considered as the major challenge in this process. The following subsections will discuss some of strategies employed in this stage based on the literature.

2.2.1 Hough transformation

The Hough transformation strategy in character segmentation is based on finding lines in the image space. In other words, the existence of number of neighbouring pixels indicates the existence of a line. The searching process is performed in the parameter space instead of the image space. Each pixel in the image space is translated to a curve in the parameter space. Therefore, the search process in the parameter space is built on finding curves that cross the same point. These curves indicate that their related pixels in the image space are on a line [16].

2.2.2 Connectivity component

Pixel connectivity component is the most used technique in segmenting characters from the vehicle plate. It is basically based on detecting linked pixel regions in the binary image. In this algorithm, the process starts by scanning the processed image after converting it to a binary image from top left to bottom right [4]. It identifies all pixels belong to each connected region (i.e. character).

2.2.3 Horizontal and Vertical projection

The histogram technique can be exploited in character segmentation as well. In this concept, a horizontal histogram is applied to the LP to detect its characters. This step is built on finding relevant pixels that construct each character in the LP. Afterward, the detected characters are separated by implementing the vertical histogram [17].

2.3 LP character recognition

This stage concerns identifying the extracted plate characters. Character similarity and font variation are the most common difficulties encountered and impacting on the accuracy of this stage. A variety of techniques have been used in the field of licence plate recognition to identify the segmented characters. Although each technique has shown a capability in dealing with this issue, reasonable results remain unreachable. This is because of the difference (e.g. size and shape) between the segmented character and the compared database. The most commonly used techniques for this stage are described in the following subsections. [18].

2.3.1 Neural Network

Multilayered Perceptron (MLP) is an artificial neural network model that has been used in classifying the datasets. In particular, MLP is very popular in recognizing the characters. In its basic architecture, MLP consists of input layer (a training set of images is passed to the model in this layer), hidden layer (computations are performed in this layer) and output layer (the decision is made in this layer) [19][20].

2.3.2 Template Matching

This technique is based on using a database of templates which represent all possible characters that can appear in the targeted licence plates. For each character obtained from the previous LPR phase (i.e. segmentation phase), a comparison process is performed. In this process, a correlation coefficient is calculated between the segmented character and each template. The highest correlation coefficient indicates the best template match for the segmented character [5][4].

2.3.3 Markov model

Markov models are one of the powerful tools in the field of pattern recognition. It simply is an automata of finite number of states linked with probabilistic transitions. A Markov model has the ability to recognize the text either character by character or word by word [21][6].

2.3.4 Support vector machine

Support Vector Machine (SVM) is another popular technique in character recognition. It is a supervised learning algorithm for classification. In terms of character recognition, the segmented characters are passed into the SVM classifier after training it with collection of known characters [22][23].

3 PROPOSED LIBYAN LPR SYSTEM

The candidate LPR system involves several stages as can be shown in Figure 2. The following subsections explain the proposed LPR system in more details.

3.1 Pre-processing

The pre-processing phase is a vital step in any image processing system. It concentrates on simplifying the whole process by performing various operations such as converting the RGB images to grey-scale images and then dilating them.

3.1.1 Grey-scale Image Transformation

The pre-processing stage begins with converting the input true colour image to a greyscale image. Each pixel (n, m) in the colour image contains three components; R for red, G for green and B for blue [20]. The conversion is simply performed by implementing a pixel-wise transform as follows.

$$I_{grey\_scale}(n, m) = 0.2989 * I_{colour}(n, m, R) + 0.5870 * I_{colour}(n, m, G) + 0.1140 * I_{colour}(n, m, B) \quad (1)$$

where I_{colour} is the colour image and $I_{grey\text{-}scale}$ is the converted grey scale image [15].

3.1.2 Image Dilation

Converting the RGB image to grey-scale image caused some changes in the image such as losing features that related to its objects' edges. Therefore, a dilation process is performed to improve the image of interest by joining the broken edges. In this operation, if the pixel of interest is located at a broken edge and at least one of its neighbours is not, the broken edge at this pixel is expected to be fixed [15]

3.2 LP Localisation

As shown in Figure 2, license plate localisation process involves four stages, which are processing the horizontal and vertical edges, passing histograms through a low pass digital filter, filtering out unwanted regions and region of interest extraction. Each of these stages is described in more detail below.

3.2.1 Constructing Horizontal and Vertical Histograms

In this stage, horizontal and vertical histograms are constructed for the processed greyscale image. In the horizontal histogram, the total sum of the intensity differences is calculated for each column. In the first column for example, the process starts with initialising the total sum of the intensity differences and subtracting the first pixel from the second one. The result is added to the total sum of the intensity differences if it exceeds a certain threshold. These certain steps are performed for each pixel (n, m) and its neighbour $(n + 1, m)$ till the end of the first column is reached. When this process has taken place on all image columns, we end up with a horizontal vector of values representing the sum of the intensity differences per columns (i.e. horizontal histogram) as shown in Figure 6(a). The vertical histogram is constructed by using a similar technique (the process explained earlier is performed between row neighbour pixels). In this case, a vertical vector of the total sum of intensity differences per rows is obtained (i.e. a vertical histogram) as shown in Figure 7(a).

3.2.2 Filtering the Histograms

Filtering the histograms is considered a vital step in this system. It smooths out the drastic changes that are visible in the histograms and caused by the disturbed noise (e.g. Figure 6(b)). The filtering process is performed by passing the histograms through a low-pass filter. Each histogram value is replaced by its average with some neighbour pixels in both sides. Afterwards, histogram low values are removed by implementing a band-pass filter and replaced with zeros as shown in Figure 6(c).

3.2.3 Removing Unwanted Regions from the Processed Image

Since the LP in the processed greyscale image consists of alphanumeric characters written on a background of different colour, the LP is expected to present high intensity variation between neighbour pixels. In addition, intensity variation is also present in some other areas of the processed image and this could be caused by illumination conditions and some other factors. These particular areas of interest in turn to show high horizontal and vertical histogram values. Therefore, a filter with a dynamic threshold is applied to keep them and remove the rest as can be seen in Figure 8.

3.2.4 Region of Interest Extraction

As shown in Figure 8,the previous phase in the localisation process produced a number of regions of interest. These regions all have the probability of containing the LP based on their high histogram values. At this stage, the region of the maximum horizontal and vertical histogram values is detected and considered to contain the LP as in Figure 9.

3.3 Character segmentation

To be able to implement the connected component analysis technique, the detected LP is converted to a binary image. This technique as explained in Section 2.2.2 is performed using a window which crosses the binary image to detect all linked regions. These regions of interest are generated as rectangles each of which contains a single LP's character as shown in Figure 10.

3.4 Character recognition

Before proceeding to the last phase in the proposed LPR system, a dataset of 10 templates was constructed. Each template contains a binary image representing one of the used numbers in the Libyan vehicle license plate (i.e. 0-9).

The key process in this phase concentrates on taking each segmented character identified from the previous phase (i.e. LPR character segmentation) and comparing it with all dataset templates. The comparison is based on calculating the correlation coefficient between the segmented character and the template. Therefore, for each segmented character 10 correlation coefficients were achieved, and then the template with the highest correlation coefficient has the most similarity with the segmented character.

Note that: at the segmentation phase, the Arabic word ليبيا is usually identified as one object (i.e. character) as its pixels are all connected. Thus, when this word is checked at the recognition phase and compared with the character datasets the correlation coefficient equals or nearly to zero. This leads to ignoring the result of comparing this word and any segmented object which is not a character.

4 EXPERIMENTAL RESULTS AND DISCUSSION

In this work, the proposed LPR system was implemented using the Matlab R2012a software. A dataset contains 200 RGB images for vehicles with several properties such as colours, background contents, plate sizes and varying intensity of light to test the effectiveness of the proposed LPR system (Figure 11). 70 of the images were collected at the campus of Omar Al-Mukhtar University and 130 images were collected from various internet Web Pages. All acquired images were normalized to the size of (720 * 480) pixels.

Each pre-processed image in the dataset was first passed into the LP localisation phase (see Figure 2). In this phase, the vertical and horizontal histograms were able together to detect 174 out of 200 plates

The efficiency of each phase in this system was measured by the relation between the number of plates that were correctly processed and the total number of the plates that were passed into the phase. For the localisation phase, the accuracy is measured by the following equation:

$$LPlocalasationefficiency = \frac{correctlocalisedLP}{totalLP} \times 100 = \frac{174}{200} \times 100 = 87\%$$

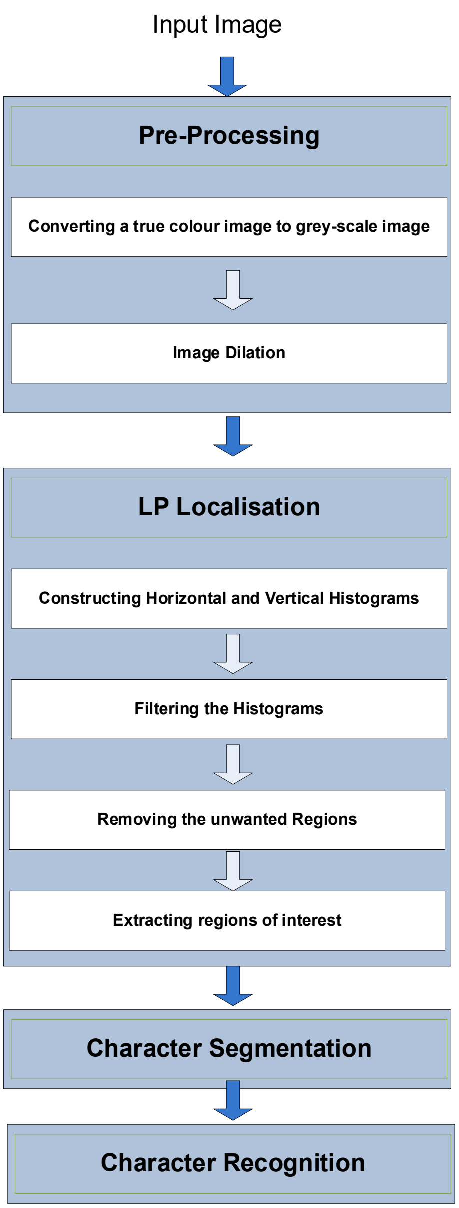

Figure 2: Proposed Libyan LPR System

Figure 3: Input true colour image

Figure 4: Grey-scale image

Figure 5: Dilated image

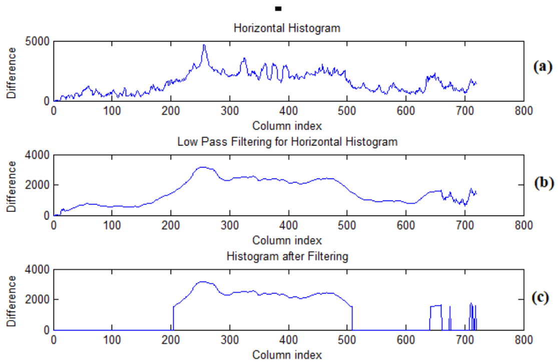

Figure 6: Horizontal Edge Processing Histogram

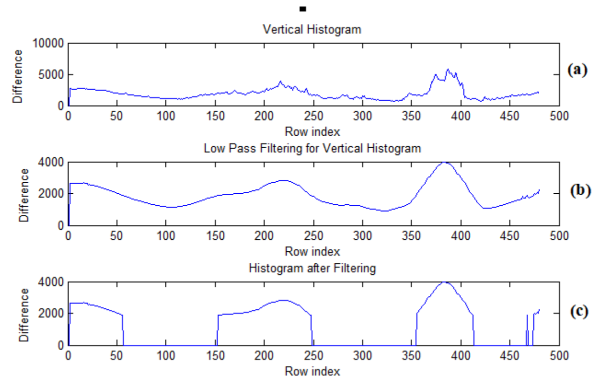

Figure 7: Vertical Edge Processing Histogram

Figure 8: Image segmenting

Figure 9: Detected license plate

Figure 10: Character segmentation

Therefore, the LP localisation efficiency is 87%. The reason behind this restricted accuracy in the localisation results may be attributable to the distortion in the used license plates (it is a quiet difficult for the projection histogram based method to perform well when the LP extremely distorted).

For the segmentation phase, the inputs were restricted to the plates that were correctly detected (i.e. 174). The connected component analysis technique successfully segmented 156 out of 174 license plates (i.e. 90%).

In the recognition phase, the proposed system correctly recognised the characters of 134 plates out of 156 (i.e. 86%). It was observed that the template matching method failed to recognise some segmented characters due to the poor condition of the most used LPs. This is also caused by the presence of some marks in the LP (e.g. screws that used to secure the LP) which made it difficult to identify the segmented characters correctly when compared to the template. Generally, the accuracy achieved here by template matching method is still quite reasonable. Table I summarise the accuracy rate of each phase of the proposed LPR system.

5 THREATS TO VALIDITY

The main threat to validity of this study is the dataset size where only 200 RGB images were used. However, authors aim to mitigate this threat in the near future by exploring data augmentation approaches to generate more data instances. In addition, the reported LPR system in this study was used only for stationary vehicle scenarios (e.g. car parks) but this is relatively early work and a new application in Libya; the authors aim to extend this work by considering different case scenarios such as motorways.

6 CONCLUSION

In the reported work, localisation, segmentation and recognition system for Libyan license plate was presented. Vertical and horizontal projection histograms were implemented to locate the plate. The connected pixels algorithm was applied to separate the plate characters. Afterwards, the extracted characters were recognised using the template matching method. This proposed system achieved accuracy of 87% at the localisation phase, 90% at the segmentation phase and 86% at the recognition phase.

Despite of the initial achievements of the proposed system, further work is required for the system to become practically usable in Libya: for instance the accuracy of the localisation and recognition phases may be improved by using deep learning approaches.

Figure 11: Sample input images

Table 1: Test Results

LPR Phase	Success rates (%)
LPR Localisation	87%
LPR Segmentation	90%
LPR Recognition	86%

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