A Fast Algorithm for License Plate Detection

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***Abstract*- License Plate Recognition (LPR) is one of the most important types of intelligent transport system and is of considerable interest because of its potential applications to many areas such as highway electronic toll collection, traffic monitoring systems and so on. It was developed to identify vehicles by the contents of their license plate. Research is in progress for the recognition of Korean, Chinese, European and other license plates. In this paper, we will describe a fast algorithm for automatic license plate detection system for the Egyptian license plates that achieves a high detection rate without the need for a high quality images from expensive hardware. The system captures images of the vehicles with a digital camera. An algorithm for the extraction of the license plate has been explained and designed using Matlab. We achieved about 96% detection rate for small dataset.**

***Keywords*- license plate detection (LPD), license plate segmentation, license plate recognition (LPR), principal component analysis (PCA).**

I. INTRODUCTION

Monitoring vehicles for law enforcement and security purposes is a difficult problem because of the number of automobiles on the road today. An example is this lies in border patrol: it is time consuming for an officer to physically check the license plate of every car. Additionally, it is not feasible to employ a number of police officers to act as full-time license plate inspectors. Police patrols cannot just drive in their cars staring at the plates of other cars. There must exist a way for detecting and identifying license plates without constant human intervention. As a solution, we have implemented a system that can extract the license plate number of a vehicle from an image given a set of constraints.

In any object recognition system, there are two major problems that need to be solved (i) detecting an object in a scene and (ii) recognizing it; detection being an important requisite. In our system, the quality of the license plate detector is doubly important since the make and model recognition subsystem uses the location of the license plate as a reference point when querying the car database.

This paper is organized as follows: section-II presents general constraints and data collections, section-III introduces the LPR problem, section-IV gives a brief discussion of previous work, section-V discusses the proposed technique, section-VI introduces the results and conclusions, while, section-VII contains future work.

II. CONSTRAINTS AND DATA COLLECTION

A. Constraints

Due to the limited time interval; a set of constraints have been placed on the system to make the algorithm more manageable. These constraints are: (i) use a digital camera; (ii) image of the vehicle taken with variable angles; (iii) image of the vehicle taken from fixed distance (about 1-2 m); (iv) vehicle is stationary when the image was taken, (v) only Egyptian license plates will be processed; Fig.1.

Fig.1 An example of Egyptian license plate of dimensions is 40×16 cm

B. Data Collection

The images of vehicles were taken with a benq digital camera, with three different resolutions. On average, the images were taken (1-2m) away from the vehicle. They were stored in color JPEG format on the camera. We use Matlab to convert the color JPEG images into gray scale raw format on the PC; see Fig.2.

III. PROBLEM DEFINITION

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. These problems, and the changing weather conditions, are what make the field of License Plate Recognition a good candidate for testing Pattern Recognition techniques [1].

Fig.2 an Example of the Acquired Data

IV. PREVIOUS WORK

Most LPR systems employ detection methods such as corner template matching [2] and Hough transforms [3, 4] combined with various histograms based methods. Kim et al. [5] take advantage of the color and texture of Korean license plates (white characters on green background, for instance) and train a Support Vector Machine (SVM) to perform detection. Their license plate images range in size from 79 × 38 to 390 × 185 pixels, and they report processing low-resolution input images (320 × 240) in over 12 seconds on a Pentium3 800MHz, with a 97.4% detection rate and a 9.4% false positive rate.

Simpler methods, such as adaptive binarization of an entire input image followed by character localization, also appear to work as shown by Naito et al. [6] and [7], but are used in settings with little background clutter and are most likely not very robust. Since license plates contain a form of text, we decided to face the detection task as a text extraction problem. Of particular interest to us was the work done by Chen and Yuille on extracting text from street scenes for reading for the blind [8]. Their work, based on the efficient object detection work by Viola and Jones [9], uses a strong classifier with a good detection rate and a very low false positive rate. We found that this text detection framework also works well for license plate detection. When we use color based filter there are some problems license plate comes in different color according d to the type of driving license.

The Saudi Arabian License plate recognition [10] used a recognition algorithm based on width to height ratio but there are many problems in this method: (i) width to height ratio is differs from a car to another depending on the distance between the camera and the car; (ii) small vertical edges will difficult the recognition problem because it change the width between edges, and (iii) when we use different view this will remove desired vertical edges,(v) There are many objects in the image achieves equal width to height ratio.

V. The Proposed Technique

In this section the proposed algorithm will be explained then applied to the Egyptian license plate, the algorithm has four steps: (A) Histogram Equalization (B) Removal of Border and Background (C) Image Segmentation (D) License Plate Detection.

A. 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. To increase the contrast of the gray scale image from the PC, histogram equalization is used; we will use this step for low contrast images only, see Fig.3.

B. Removal of Border and Background

As with the license plate recognition problem, detecting the car is the first step to performing make and model recognition (MMR). To this end, one can apply a motion segmentation method to estimate a region of interest (ROI) containing the car. This method would also be useful for make and model recognition in static images. We first convert image to black and white then use Matlab to remove border of the image.

Fig.3 Car after getting histogram equalization

Fig.4 Sobel vertical edges

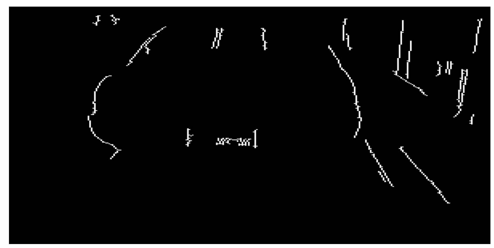

Fig.5 Vertical edge regions

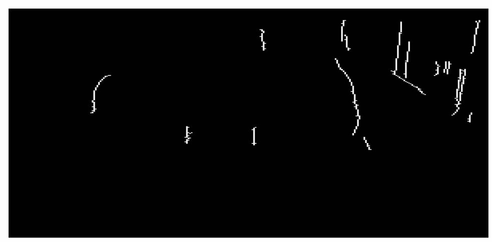

Fig.6 Image after removing small elements

The proposed system 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 input 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 edges; see Fig. 4,5, and 6. Hence, get the horizontal edges using Sobel edge detection function for the upper and the bottom and the removes the area outside wide horizontal edges; Fig.7. On the other hand, Fig.8 shows the reduced form of horizontal edges [11, 12].

C. Image Segmentation

i. Often the license plate will be in the lower half of the image so we will remove upper half of the image (we can use the lower 1/3 of image, for safety we will use lower half).
ii. After these steps new image will be about 1/3 original image so the recognition algorithm will be very fast; Fig.9

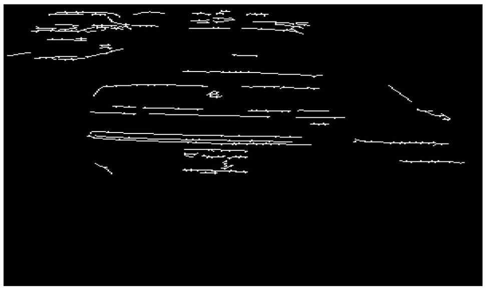

Fig.7 Horizontal edges after removing small elements

Fig.8 Car after removing border and background

Fig.9 Image after segmentation

D. License Plate Detection

1. Features Extraction

Feature extraction is the transformation of the original data (using all variables) to a data Set with a reduced number of variables. In the problem of feature selection, the aim is to select those variables that contain the most discriminatory information. Alternatively, we may wish to limit the number of measurements we make, perhaps on grounds of cost, or we may want to remove redundant or irrelevant information to obtain a less complex classifier.

In feature extraction, all variables are used and the data are transformed (using a linear or nonlinear transformation) to a reduced dimension space. Thus, the aim is to replace the original variables by a smaller set of underlying variables. There are several reasons for performing feature extraction: (i) to reduce the bandwidth of the input data (with the resulting improvements in speed and reductions in data requirements) ;(ii) to provide a relevant set of features for a classifier, resulting in improved performance, particularly from simple classifiers; (iii) to reduce redundancy;(v) to recover new meaningful underlying variables or features that the data may easily be viewed and relationships and structure in the data identified [11].

Wavelets have been demonstrated to give quality representations of images [12]. The discrete wavelet transform (DWT) presents a multiresolution analysis in the form of coefficient matrices which can be used in a manner similar to Fourier series coefficients. This DWT representation can be thought of as a form of "feature extraction" on the original image, we will use Haar-like features, where sums of pixel intensities are computed over rectangular sub-windows [9].

2. Principal Component Analysis

Principal components analysis (PCA) originated in work by Pearson (1901). It is the purpose of principal components analysis to derive new variables (in decreasing order of importance) that are linear combinations of the original variables and are uncorrelated. Geometrically, principal components analysis can be thought of as a rotation of the axes of the original coordinate system to a new set of orthogonal axes that are ordered in terms of the amount of variation of the original data they account for [11]

In some situations, the dimension of the input vector is large, but the components of the vectors are highly correlated (redundant). It is useful in this situation to reduce the dimension of the input vectors. An effective procedure for performing this operation is principal component analysis. This technique has three effects: (i) it orthogonalizes the components of the input vectors (so that they are uncorrelated with each other), (ii)it orders the resulting orthogonal components (principal components) so that those with the largest variation come first, (iii) and it eliminates those components that contribute the least to the variation in the data set [12].

Chen and Yuille argue that, while this technique may be useful for face detection, text has little in common with faces [8]. To support their assumption, they perform principal component analysis (PCA) on their training examples and find that about 150 components are necessary to capture 90 percent of the variance, whereas in typical face datasets, only a handful would be necessary. It is desirable to select features that produce similar results on all license plate images and are good at discriminating between license plates and non-license plates.

3. Artificial Neural Networks (ANNs)

Neural networks have been shown to be excellent classification devices because of their inherent learning ability [13, 14]. Multilayer topologies are capable of learning non-linear decision boundaries, a fact which increases the versatility of neural networks to solve real-world. One type of "reduced-weight" architecture is called the locally-connected, weight-sharing network.

Notice that the hidden layer nodes only accept "local" information from the inputs. This type of architecture allows us to use the neural network as a local feature extractor, which in turn, also reduces the set of weights in the network. The weight-sharing characteristic involves grouping hidden layer nodes into "feature maps", where each node within the map accepts inputs from different sections of the input layer. These nodes can then share the same synaptic weights, and therefore, look for the same "features" in different parts of the input matrix. This allows for even further reduction in network parameters. The locally-connected, weight-sharing network architecture is of great benefit when applied to texture classification. We approached the license plate detection problem as a text extraction problem [8].

The method we employ for detecting license plates can be described as follows. A window of interest, of roughly the dimensions of a license plate image, and the image contents are passed as input after getting haar features and PCA to a single layer neural network (weak classifier) whose output is 1 if the window appears to contain a license plate and 0 otherwise. The window is then placed over all possible locations in the frame and candidate license plate locations are recorded for which the classifier outputs a 1 then use it as an input for multilayer neural network (strong classifier) Fig.10, and 11.

Since the size of a license plate image can vary significantly with the distance from the car to the camera, using a fixed-size window of interest is impractical. Window-based detection mechanisms often scan a fixed-size window over a pyramid of image scales. Instead, we used three different sizes of windows, each having a custom-trained strong classifier for that scale. Scanning every possible location of every frame would be very slow were it not for cascaded classifiers, the cascaded classifiers greatly speed up the detection process, as not strong classifier need be evaluated to rule out most non-license plate sub-regions, see also Fig.12.

ANN method here will not consume more computational time because of many reasons. first ANN technique will apply on the segmented image which is about half size of the original image or less but in other techniques they apply ANN on all size of the image .second here we use sequential weight bias training function (matlab function called trains) instead of Levenberg-Marquardi back propagation(trainlm)function , matlab default learning function, and this gives us more speed and accuracy than any other training function. Third reason is the use of PCA which reduce the number of features to every image so the system will run in fast mode and give best result .

VII. Conclusion & Results

Our LPD solution is real-time and works well with inexpensive camera hardware and does not require infrared lighting or sensors as are normally used in commercial LPR systems. We tried to overcome most problems occurred in LPD systems. Many problems appear through this work such as different fonts and size of the Egyptian license plate would difficult the classification process, there no database for Egyptian license plate and there is no standard license plate in Egypt. We achieved 96% detection rate for small dataset (about 30 images).we compare our proposed technique with some technique and we found that this technique is fast and efficient.

VIII. Future work

Modern FPGA platforms provide the hardware and software infrastructure for building a bus-based system on chip (SoC) that meet the applications requirements. The designer can customize the hardware by selecting from a large number of pre-defined peripherals and fixed IP functions and by providing new hardware, typically expressed using RTL. In order to accelerate the system we can implement ANN classifier using FPGA with parallel processing instead of using Matlab .we expect that we can achieve an overall LPR system speed up.

We can get correlated features between all images after applying PCA to every image this can help us to reduce the input features to ANN which will speed it up .

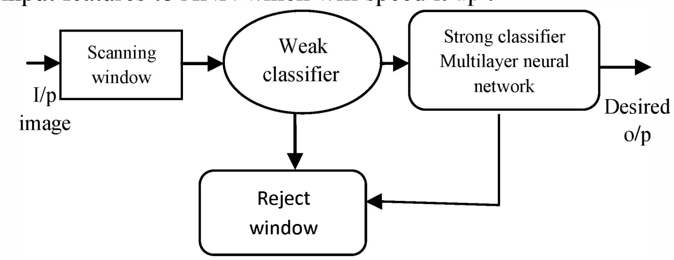

Fig.10: A cascaded classifier. The early stage is very efficient and good at rejecting the majority of false windows.

Fig.11 apply ANN with adaptive sub window

Fig.12.Final output

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