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Survey on License Plate Localization using Genetic Algorithm and Temporal Redundancy

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Abstract: *License Plate Recognition plays an important role in real world applications such as automatic toll collection, access control in private parking lots, stolen vehicles identification and traffic surveillance. Recognition of an on-road vehicle using its license plate is an important task performed by several intelligent transportation systems around the world. This task is known as Automatic License Plate Recognition. This paper is a survey of license plate Recognition based on temporal redundancy and genetic algorithm integrated with image thresholding. ALPR using temporal redundancy discusses mainly about temporal redundancy approach along with two post processing techniques. Genetic algorithm on the other hand, executed the license plate region detection of the digital image which depends on the set-level of the image threshold values obtained.*

Key Words: ***Automatic license plate recognition, vehicle classification, Genetic Algorithm, GRM, CCAT, and Image Thresholding***

1. INTRODUCTION

It is believed that there are currently more than half a billion cars on the roads worldwide. All those vehicles have their vehicle identification number as their primary identifier which is mounted onto its body and no vehicle without properly mounted, well visible and well readable license plate should run on the roads. With increasing number of vehicles on roads, it has become difficult to manage traffic rules for smooth traffic flow. Vehicles in each country have unique license number which can be seen on the license plate. This number helps to distinguish one vehicle from other. An automated system can be implemented to identify the vehicle number plate and extract the character from the region containing the license plate. The number recognised from the license plate can be used to retrieve information about the vehicle and its owner which helps in further processing.

2. PROPOSED SYSTEM

2.1 Temporal Redundancy Approach

ALPR based on temporal redundancy involves:

2.1.1 ALPR Pipeline
2.1.2 Temporal Redundancy Aggregation
2.1.3 Vehicle Appearance Classification
2.1.4 Tree Based Query

2.1.1 ALPR Pipeline

We first detect the vehicle and then its license plate, located inside the vehicle patch. To solve both tasks, we employ a sliding window approach composed of a classifier based on Support Vector Machines (SVM) and Histograms of Oriented Gradient (HOG) as feature descriptors. Once the license plate has been located, we need to segment the image into multiple patches containing license plate characters (LPCS). . In this approach, instead of using a single threshold to perform license plate binarization using the Otsu method, we consider a set of different values.

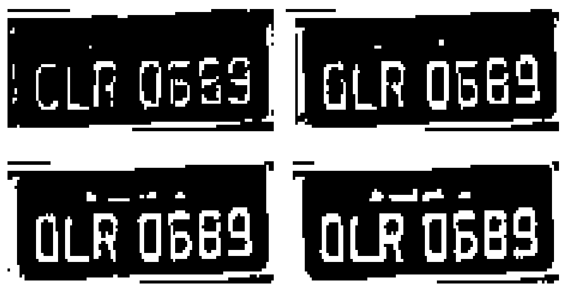

Fig. 1: Samples of the license plate considering different thresholds, 5 and 10 on the top images and 20 and 30 on the bottom images.

2.1.2 Temporal Redundancy Aggregation

We combine the individual recognition results using two main approaches: (i) majority voting and (ii) average of the classifier confidence.
While the former takes all predictions for each frame and assumes that the most predicted character for every license plate position is the correct, the latter averages the classes by minimizing the intra-class variance.

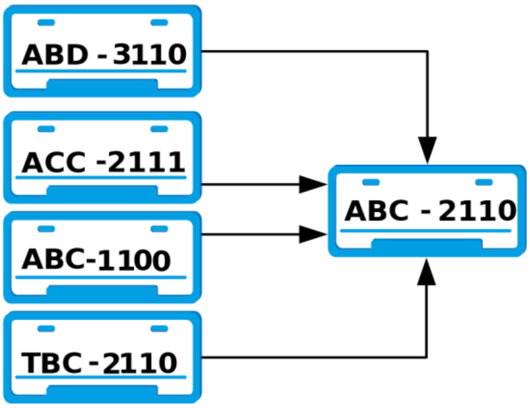

Fig. 2: The proposed approach combines results of multiple frames to improve the vehicle recognition rate.

2.1.3 Vehicle Appearance Classification

Once we have the vehicle location in multiple frames, we recognize its appearance, which is used then to query the license plate database, and retrieve the license plates belonging to vehicles with that appearance. The use of vehicle appearance instead of the recognized license plate itself to select candidates can help the ALPR to discard those candidates that have license plates similar to the correct one but belong to different vehicles models.

Fig. 3: Two different vehicle models presenting very similar frontal appearance. Voyage (left) vs. Gol (right).

2.1.4 Tree Based Query

Once the license plate has been recognized by the temporal redundancy ALPR, we sort the recognized characters by the OCR confidence and, from the most to the least confident character, we filter those license plates that do not have that same character on that particular position. If we find a group having only a single license plate, we assume that this is the correct license plate. Otherwise, if we do not have any license plate at some iteration, we return one level of the filtering and choose a license plate that is the most likely to the correct one using the OCR confidence.

2.2 Genetic Approach

Use of a new genetic algorithm (GA) approach is introduced to detect the locations of license plate (LP) symbols. An adaptive threshold method is being used to overcome the errors happening due to changes of illumination conditions while converting the image into binary. To detect the candidate object inside the unknown image an image processing technique, connected component analysis technique (CCAT) is used. To simplify the system adaptability when applied in different countries, a scale-invariant geometric relationship matrix is introduced to model the layout of symbols in any LP. Along with that, two new crossover operators, based on sorting, are being used, which improve the convergence speed of the system very much. Most of the problems faced by CCAT techniques such as broken bodies, are minimized by modifying the Genetic Algorithm used to perform partial match until reaching an acceptable fitness value.

This section is an overview of the proposed system. The proposed system contain two phases: image processing phase and GA phase.

GA selects the optimum License Plate character location depending on the input geometric relationship matrix that defines the geometrical relationships between the symbols in the concerned LP.

2.2.1 Image Processing Phase

In this phase, the input color image will undergo a sequence of processes to extract the relevant 2-D objects that may represent the symbols constituting the license plate. The main steps in image processing phase are given below:

1. Color to Grey-scale: The captured color image is converted to corresponding grey-scale image for extracting the relevant information from the picture. The conversion is done by the standard NTSC method. The equation for conversion is:

$$gs = 0{:}299R + 0{:}587G + 0{:}114B \qquad (1)$$

2. Grey to Binary: The Grey-scale image that obtained in above step is then converted to binary image. It is the most sensitive stage in the localization of license plate number due to spatial and temporal variations in the plate. In this system, a local adaptive method has been implemented to determine the threshold at each pixel dynamically depending on the average grey level in the neighborhood of the pixel. If the pixel intensity is lesser than 0.8 of the local mean, it is assigned to the foreground; otherwise, it is assigned to the background. The 0.2 offset below the mean is chosen experimentally to minimize the sensitivity to fluctuations in illumination.

3. Connected Component Analysis: Connected component analysis is a technique in image processing that scans an image and groups pixels in labelled components based on pixel connectivity. An eight point CCA is used here to identify and separate the components in the binary image. The output of this stage is an array of size N.

4. Size Filtering: The objects extracted from the previous stage are filtered on the basis of their widths and heights such that the width and height of the LP symbols lie between their respective thresholds as follows:

$$Wmin<=Wobj<=Wmax \quad (2)$$
$$Hmin<=Hobj<=Hmax \quad (3)$$

where H(min) and W(min) are the values below which a symbol cannot be recognized and W(max)can be set to the image width divided by the number of symbols in the license number. H(max) is calculated as W(max) divided by the aspect ratio of the used font. The output of this stage is an array of M-objects.

5. Color Feature Extraction: This step deals with extraction the color features of the input image by converting the RGB colors to HLS values. The RGB model is pretty good for color representation on a color monitor. But, human visual system is less sensitive to change in color than to changes in brightness, so convert RGB image data into a color space that treats tint, shade and tone. The HLS model is three dimensional color space which consists of Hue, Lightness and Saturation. There are equations to calculate these three parameters.

2.2.2 Genetic Algorithm Phase

In the following sections, the formulation of the GA phase to resolve the 2-D compound object detection problem will be introduced in detail, indicating the encoding method, initial population setup, fitness function formulation, selection method, mutation and crossover operator design and parameters setting. The genetic algorithm phase also includes the output from color feature extraction of the input color image.

1. Chromosome Encoding: Encoding of a compound object such as the LP is accomplished based on the constituting objects inside it. Since the next step after plate detection is to recognize the license number, the main symbols identifying the plate number should be included as a minimum. In the case of the recent Saudi-LP, for example, there are four Arabic digits and three English letters. Other symbols in the LP can be added to extend the representation for more layout discrimination if needed. In our experiments, only the seven symbols (four digits and three letters) are used to detect the LP number.

2. Fitness Function: The proposed fitness is selected as the inverse of the calculated objective distance between the prototype chromosome and the current chromosome .Considering the two objects O1 and O2, the position relationship is defined in the two direction by following formulas:
$RX1 = (X2 – X1) / H$
$RX2 = (Y2 – Y1) / H$
Placing the values of the different relationships in one matrix, produces what we call the geometric relationships matrix (GRM). Table I presents the values of the geometric relationships matrix (GRM) for the Saudi LP shown in Fig. 3; where the variable j denotes the index of each symbol from left to right. The color features which are extracted, then used here to find out the ultimate fitness value.

3. Selection Method: In our system, the stochastic universal sampling (SUS) method has been adopted for the selection of offspring in the new generation. In the SUS method, each individual is mapped to a continuous segment of a line equal in size to its fitness as in roulette-wheel selection. Then, a number of equally spaced pointers are placed over the line depending on the percentage of individuals to be selected. In our system, individuals of 90% of the population size (0.9 Z) are selected to be exposed to mutation and crossover operators.

4. Mutation Operator: Mutation is needed because successive removal of less fit members in genetic iterations may eliminate some aspects of genetic material forever. By performing mutation in the chromosomes, GAs ensure that new parts of the search space are reached to maintain the mating pool variety. Here implemented two types of interchangeably used mutation operators, substitution operator and swap operator.

5. Crossover Operator: There are many methods used to implement the crossover operator. For instance, single-point crossover, two-point crossover, n-point crossover, uniform crossover, three-parent crossover, alternating crossover and so on. Since in the case of LP detection problem, GA is used to search for a sequence of objects having nearly the same y-position and placed in order according to their x-positions, then the problem can be gradually solved by dividing the recombined chromosome's objects according to their y-positions into two groups and then sorting each group (constituting a chromosome) according to the x-positions. By following the above discussion, a new crossover method has been proposed that depends mainly on sorting as follows:

- The two parent chromosomes are combined into one longer array C-array that includes a number NC of non-repeated genes.

- The genes inside C-array are sorted in ascending order according to the Y-coordinate of the object corresponding to each gene.
- C-array is scanned from left to right starting from index 1 to L, to construct the first child giving it the first L genes.
- C-array is scanned from left to right starting from index NC L + 1 to NC to construct the second child giving it the last L genes.
- Each child is sorted in ascending order according to the X-coordinate of each genes object to produce the final shape of each child.

6. Elimination: In this step, the genes which are considered to be as the part of license plate number are eliminated by comparing with the intensity of adjacent genes and some threshold values. By doing elimination, the speed of the system can be increased and localization can be done more accurately.

3. EXPERIMENTAL RESULTS

3.1 Genetic Approach

[1] This paper showed that the plate localization method using Genetic Algorithm and Image thresholding successfully located the vehicle's plate area. There were some modifications made in order to incorporate Image thresholding and GA for plate localization. The image's threshold value can be adjusted to suit the required application for the camera depending on the time of the day. It was seen that the configurations tested successfully converges to the location of the plate area. The time it takes for the GA to locate the plate area is found to be at about 3.733000 s for the algorithm. For the accuracy of the algorithm, the algorithm was tested on several images exhibiting single plate card on each image. Out of 86 images, 82 images were correctly evaluated which yield an accuracy of 95.34883%. Results show; that the proposed plate localization method is accurate and robust.

[2]The GRM matrix to adapt our system on this different layout as shown in Table III. Results of our experiments are summarized in the first three rows in Table IV; where false positive (FP) means assigning incorrect locations to LP symbols. Surely the remaining undetected cases are false negative (FN) cases where each image includes an LP but the ODT test is not met for all combinations of objects in the tested images.

TABLE II: GRM FOR THE GREECE LP.

j	1	2	3	4	5	6
$RX_{j+1,j}$	0.8	0.8	1.55	0.8	0.8	0.8
$RY_{j+1,j}$	0	0	0	0	0	0
$RW_{j+1,j}$	0	0	0	0	0	0
$RH_{j+1,j}$	0	0	0	0	0	0

TABLE III: RESULTS OF OUR EXPERIMENTS

Exp #	Number of test samples	Detected without skipping	Detected with skipping	False negative N#(rate)	False positive N#(rate)	Success rate
1st(ours)	800	738	52	8 (1%)	2 (0.25%)	98.75%
2nd(ours)	335	297	30	6 (1.79%)	2 (0.59%)	97.61%
1&2(ours)	1135	1035	82	14 (1.23%)	4 (0.35%)	98.41%

3.2. Temporal Redundancy Approach

Recognition rates achieved

Approach	Manual	Automatic
Without redundancy	78.3%	66.3%
Redundancy with OCR avg	93.6%	77.9%
Redundancy with majority voting	94.6%	81.8%

4. CONCLUSION

The main part of this proposed system is the usage of Genetic Algorithm (GA). The License Plate (LP) which may contain unwanted information on a plate. These may firstly remove by the image processing phase and then localized by the genetic algorithm phase. This system possessed high immunity to changes in illumination either temporarily or spatially to a high percentage success rate was achieved with the aid of the adaptability aspect of the Gas. Also, an enhancement in the performance of the developed GA was achieved by applying the new USPS crossover operators, which vary greatly improved the convergence rate of the whole system. While, the system proposed in temporal redundancy is a new approach to perform real-time ALPR exploring temporal redundancy information from detected vehicles. The system demonstrated that it is possible to can improve the results by 15.5 p.p. using multiple frames to identify the vehicle. In addition, it showed that it is possible to achieve 89.6% of recognition rate. So, therefore by combining these 2 approaches we can attain a higher efficiency in detection of license plate.

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