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Review on Localization of License Plate Number Using Dynamic Image Processing Techniques and Genetic Algorithms

Authors

Kiran Kondlekar[1], A. S. Shirsat[2]

[1]Savitribai Phule Pune University, Smt. Kashibai Navale College of Engineering Pune, Vadgaon BK,411041

Email: *Kkondlekar31@gmail.com*

[2]Asst. Prof, EXTC Department, Smt. Kashibai Navale College of Engineering, Savitribai Phule Pune University, Pune, Vadgaon BK,411041

Email: *Asshirsat.skncoe@sinhagad.edu*

Abstract

Automatic license Plate Recognition (ALPR) is the method of extracting vehicle license plate information from an image or a sequence of images. A design of a new Genetic Algorithm (GA) is introduced to detect the locations of the License Plate (LP) symbols. The extracted information can be used with or without a database in number of application applications, such as electronic payment systems, toll payment, parking fee payment and freeway and arterial monitoring systems for traffic surveillance. The ALPR uses either a color, black and white, or infrared camera to take images. The quality of the acquired images is a major factor in the success of the Automatic License Plate Recognition. Connected Component Analysis Technique (CCAT) is used to detect candidate objects inside the unknown image. A scale-invariant Geometric Relationship Matrix (GRM) has been introduced to model the symbols layout in any LP which simplifies system adaptability. Most of CCAT problems such as touching or broken bodies have been minimized by modifying the GA .The system as a real- life application has to quickly and successfully process the license plates. These plates usually contain different colors, and different fonts. Some plates may have a single color background and some others have background images. The license plates can be partially occluded by dirt, lighting, and other accessories on the car. The system recognizes the plate by appropriate detection.

Keywords: *Genetic algorithms (GAs), image processing, image representations, license plate detection, machine vision, road vehicle identification*

1. Introduction

License plate (LP) detection is the Most critical step in an automatic vehicle identification System. Plenty of research has been carried out to overcome many of the problems faced in this area, but there is no general method for detection of Plate which has different style and design. All the developed techniques can be categorized according to the selected features upon which the detection algorithm was based and the type of the detection algorithm itself. Color-based systems have been built to detect specific plates having fixed colors. External-shape based techniques were developed to detect the plate based on its rectangular shape. Edge-based techniques were implemented to detect the plate based on the high density of vertical edges inside it. Research in Car license plate detection based on Maximally Stable Extremal Regions (MSER) was based on the intensity distribution in the plate's area with respect to its neighborhood where the plate is considered maximally stable external region. The applied detection algorithms ranged from window-based statistical matching methods to highly intelligent-based techniques that used neural networks or fuzzy logic. GAs have been used rarely because of their high computational needs. Different research has been tried at different levels under some constraints to minimize the search space of genetic algorithms (GAs). Researchers in A recognition of vehicle license plate using a genetic algorithm based segmentation based their GA on pixel color features to segment the image depending on stable colors into plate and non-plate regions, followed by shape dependent rules to identify the plate's area. A success rate of 92.8% was recorded for 70 test samples. In Locating car license plate under various illumination conditions using genetic algorithm GA was used to search for the best fixed rectangular area having the same texture features as that of the prototype template. The used technique lacks invariability to scaling because fixed parameters have been used for the size of the plate's area. In License plate recognition based on genetic algorithm was used to locate the plate vertically after detecting the left and right limits based on horizontal symmetry of the vertical texture histogram around the plate's area. The drawback of this method is its sensitivity to the presence of model identification text or other objects above or below the vehicle that can disturb the texture histogram. Detecting license text and at the same time distinguishing it from similar patterns based on the geometrical relationship between the symbols constituting the license numbers is the selected approach in this research. Consequently, a new technique is introduced in this paper that detects LP symbols without using any information associated with the plate's outer shape or internal colors to allow for the detection of the license numbers in case of shape or color distortion either physically or due to capturing conditions, such as poor lighting, shadows, and camera position and orientation. To search for the candidate objects and to allow for tolerance in the localization process, a new genetic algorithm has been designed with a new flexible fitness function. Image processing is carried out first to prepare for the GA phase.

2. System Overview

In this section, an overview of the system is introduced. The proposed system is composed of two phases: image processing phase and Genetic Algorithm (GA) phase. Each phase is composed of many stages. Genetic Algorithm (GA) selects the optimum License Plate (LP) symbol locations depending on the input GRM that defines the geometrical relationships between the symbols in the concerned License Plate (LP). A new technique is introduced in this paper which detects License Plate (LP) symbols without using any information associated with the plate's outer shape or internal colors to allow for the detection of the license numbers in case of shape or color distortion either physically or due to capturing conditions such as poor lighting, shadows and camera position and orientation. firstly convert image into grey scale.In the binarization phase we use the Niblack's algorithm. After Morphological operations we use the Connected Component Analysis (CCA) for identifying the numbers in the image. Genetic algorithm is used for optimizing the result.

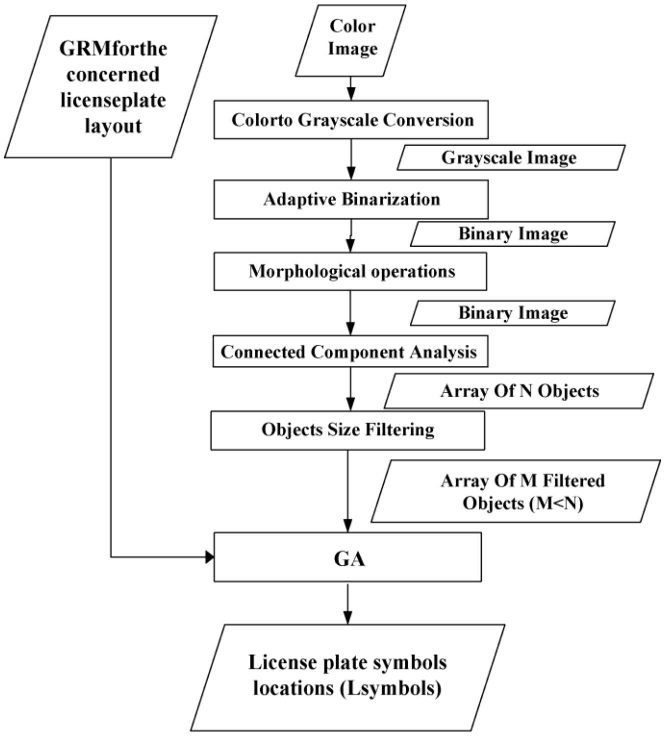

Fig. 1. Overall system Flowchart for localization of LP symbols.

2.1 Image Processing Phase

In this phase, an input color image is exposed to a sequence of processes to extract the relevant two dimensional objects that may represent the symbols constituting the LP. These processes that are carried out in different stages, will be presented in the following subsections.

2.1.1 Color to grayscale conversion

The input image is captured as a color image taking into account further processing of the image to extract other information relevant to the concerned vehicle. Color (*RGB*) to grayscale (*gs*) conversion is performed using the standard NTSC method by eliminating the hue and saturation information while retaining the luminance as follows:

2.1.2 Gray to binary using a dynamic adaptive threshold

Converting the input image into a binary image is one of the most sensitive stages in localizing LPs due to spatial and temporal variations encountered in the plate itself and the environment around it resulting in several illumination problems. Hence binarization of the image according to a fixed global threshold is not suitable to overcome these problems. In our system, a local adaptive method based on the techniques described in image thresholding has been implemented to determine the threshold at each pixel dynamically depending on the average gray level in the neighborhood of the pixel. A simple yet effective rule has been adopted to differentiate between foreground and background pixels. If the pixel intensity is higher than 90% of the local mean it is assigned to the background; otherwise it is assigned to the foreground.

2.1.3 Morphological operations

Morphological operations such as dilation and erosion are important processes needed for most pattern recognition systems to eliminate noisy objects and retain only objects expected to represent the targeted patterns. In LP detection, closing operation (dilation followed by erosion) is performed to fill noisy holes inside candidate objects and to connect broken symbols. On the other hand, opening (erosion followed by dilation) is applied to remove objects that are thinner than the LP symbols. In our system, closing is applied to fill spaces that break the bodies of symbols using a 3-pixeldisk element.

2.2 GA Phase

In this section, the formulation of the GA phase to resolve the 2D compound object detection problem will be introduced in details, indicating the encoding method, initial population setup, fitness function formulation, selection method, mutation and crossover operator design and parameters setting.

2.2.1 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, hence the main symbols identifying the plate number should be included as a minimum. Other symbols in the LP can be added to extend the representation for more layout discrimination if needed. An integer encoding scheme has been selected where each gene *i* is assigned an integer *j* which represents the index to one of the *M* objects output from the size filtering stage. The information that will be used for each object *j* is as follows:

1) The upper left corner coordinates (*X*, *Y*) of the rectangle bounding the object.
2) The height (*H*) and width (*W*) of the rectangle bounding the object.

2.2.2 Defining the fitness function

The proposed fitness is selected as the inverse of the calculated objective distance between the prototype chromosome and the current chromosome. Before clarifying how the objective distance is measured, we will show first how the geometric relationships between the objects inside a compound object are represented, followed by a discussion of parameter adaption in case of various LP detection layouts.
Compound object representation
For any two objects, we will use two types of geometrical relationships that can be defined as follows:

Position relationship:
The position relationship will be represented by the relative distances between the bounding boxes of the two objects in the *X* and *Y* directions.

Size relationship:
The size relationship will be represented as the relative differences in their bounding boxes" heights and widths.

2.2.3 The selection method

In our system, the Stochastic Universal Sampling (SUS) method has been adopted for the selection of offspring in the new generation. In 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

2.2.4 Mutation operators

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. We have implemented two types of interchangeably used mutation operators; substitution operator and swap operator as follows:

Substitution operator

In this type of operators, a random position in the chromosome is selected and the corresponding allele is changed by a new random object from the *M* available objects. The new object should be legitimate which means it does not belong to the current mutated chromosome.

Swap operator

In this operator, we implemented the reciprocal exchange mutation that selects two genes randomly and swaps them. This operator has the advantage of rearrangement of the mutated chromosome in a way that may improve its fitness by reordering of the internal objects to match the prototype‟s order.

2.2.5 Crossover operator

There are many methods to implement the crossover operator. For instance, single point crossover, two point crossover, n-point crossover, uniform crossover, three parent crossover and, alternating crossover, etc. These operators are not suitable for our problem because the resultant children will not be valid because of repeated genes that may be produced in the generated chromosomes. Also, if we prevent repetition, the resultant children„s fitness will be enhanced slowly because of the randomness of these mechanisms. An alternative solution is to design a suitable crossover operator that insures enhancement of the generated offspring. Since, in 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 chromosomes‟ objects according to their ypositions into two groups and then sorting each group (constituting a chromosome) according to the x-positions.

Following the above discussion, we propose a new crossover method that depends mainly on sorting as follows:

1) The two parent chromosomes are combined into one longer array *Carray* that includes a number *NC* of non repeated genes.
2) The underlined gene number indicates its repetition and that only one copy of it will be transferred to *Carray*.
3) The genes inside *Carray* are sorted in ascending order according to the *Y*-coordinate of the object corresponding to each gene.
4) Carray is scanned from left to right starting from index 1 to L, to construct the first child giving it the first L genes.
5) Carray 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.
6) Each child is sorted in ascending order according to the *X*-coordinate of each gene‟s object to produce the final shape of each child.

2.2.6 Replacement strategy

Many replacement strategies are used in case of replacing only a portion of the population between generations. The most common strategy is to probabilistically replace the less fit individuals in the previous generation. In elitist strategy the best fit individuals of the previous generation are appended to the current population. In our proposed system, the best 10% of the parents are selected and appended to the offspring (90%) to produce the new generation (100%).

2.2.7 Stopping criteria

The GA stops if one of the following conditions is met:

1) The best chromosome‟s objective distance (OD) is less than 5. (This value is found by trial and error).

2) The average objective distance (AOD) is not improved for 6 successive generations. In this case, the chromosome having minimum objective distance can be accepted if it is less than 8. This maximum limit will affect the allowable angle range for the detected license number

Conclusion

In this project we will prove that with effective combination of the dynamic image processing and the genetic algorithm we will identify number plates in an image by optimization. The procedure is useful in finding number plates in the given image also. Various images will be test and the system finds the localized number plate with effectiveness. a flexible system will be introduce that can be simply adapt for any LP layout by constructing its GRM matrix. The system will be prove to be invariant to object distance (scaling), insensitive with respect to perspective distortion within a reasonable angle interval, and immutable to a large extent to the presence of other types of images in the vehicle background. Due to the independency on color and the adaptive threshold used for binarization, the proposed system possessed high immunity to changes in illumination either temporarily or spatially through the plate area. Furthermore, it will be prove that although leaving some features in the compound object representation due to the variable nature of the internal objects such as the aspect ratios and the relative widths, a high percentage success rate was achieve with the aid of the adaptability aspect of the GAs. The ability of the system to differentiate between LP text and normal text will be prove experimentally. A very important achievement is overcoming most of the problems arising in techniques based on CCAT by allowing the GA to skip gradually and randomly one or more symbols to reach to an acceptable value of the objective distance. Moreover, an enhancement in the performance of the developed GA will be achieve by applying the new USPS crossover operators, which greatly improved the convergence speed of the whole system.

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