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Registration Plate Recognition from Still Images and Videos in Real Time Conditions

Glence Joseph, Dr.Tripty Singh, Andan HM, Aravind G

Department of Computer Science and engineering, Amrita School of Engineering
Bangalore, Karnataka, India

Abstract— **Registration plate recognition plays a vital role in numerous numbers of applications in today's world. Researches done so far could not completely meet the real time requirements of the system like different color, shape and size of plates, varied illumination conditions at image capture time, different positions and alignment of the plate. In the proposed system we introduce dynamic image processing techniques to meet the above mentioned short comings. We also introduce a new approach using genetic algorithm to find the location of the plate. Fluctuating illumination conditions are taken care-off by adaptive threshold method. Connected component labelling is used to identify the objects in blind folded regions. A matrix of invariant scale geometry is used for better system adaptability when applied to different plates. The convergence of the genetic algorithm is greatly improved by the introduction of a newly created mutation and crossover operators. We also modify genetic algorithm to overcome the drawbacks of connected component method by importing partial matching of the characters.**

Keywords—Image processing, genetic algorithm, adaptive threshold, connected component labelling, mutation, crossover, convergence.

I. Introduction

Registration plate recognition in real time plays a significant role in many real world applications. These systems are employed in area like parking area, restricted areas for security, traffic law enforcement, congestion control management and toll collection. The working environment of these systems differs entirely. Therefore the workaround strategy for each system differs. Previous works done are under restricted conditions like static backgrounds, non-changing illumination condition, prefixed driveways, fixed ranges of the distance between camera and vehicle. It's a very challenging problem, due to the diversity in the formats of the plate, different scales, angle of rotations and non-uniformity in illumination conditions during image acquisition. Previous works have been under limited conditions, such as fixed illumination, controlled vehicle speed, designated routes, and stationary backgrounds. License plates usually contain multiple colors, different languages are used and also different fonts, plates may have one color in the background and others with have background images. The proposed technique consists of two modules namely a license plate locating module and a license plate number identification module. License plate recognition algorithms in images or videos are generally composed of the following three steps, extract license plate region, segmentation of the plate characters and recognition of each character. Character recognition system uses morphological operations, histogram manipulation along with edge detection procedures for plate localization and characters segmentation. Morphology-based method is used to extract important contrast features as filters in finding all the likely license plate candidates after calculating motion energy from video frames. Plate recognition plays critical part in numerous applications such as unattended parking lots, security control of restricted areas, traffic law enforcement systems, congestion control, pricing and automatic toll collection. The aim of this proposal is to lessen many of these restrictions.

II. Related Work

Lotufo, Morgan and Johnson proposed automatic number-plate recognition which used optical character recognition techniques. Fahmy proposed bidirectional associative memories neural network for number plate recognition. Johnson and Bird found a knowledge-guided boundary following alongside template matching for automatic vehicle identification. Nijhuis, TerBrugge, Helmholf Pluim, and Westenberg put forward the idea of fuzzy logic and neural networks for car LPR. Fuzzy logic is used in this method for segmentation and discrete-time cellular neural networks for feature extraction. S. Hamidreza Kasaei presented a real time and robust method of license plate detection based on the morphology and template matching. Method proposed by Choi and Kim based on vertical edge using Hough transform for extracting the license plate. Artificial neural networks were adopted by P.K. Kim, E.R. Lee and H.J. Kim for extraction of color and template matching to recognize characters of license plate. The approach in which orientation map was used as a recognition feature along with a Gabor filter for recognizing characters was proposed by Saatci. W. Kim and H. Kim [6] used a genetic algorithm based segmentation to extract the region of the plate. Gabor jets projection was introduced by Yoshimura and Etoh to forms the feature vector for identifying very low resolution gray-scale character. Extracting characters without prior knowledge of their position and size in the image was done by Hontani in his proposed a method [8]. Park used color based method to extract license plate. In a survey taken by Shan Du on existing ANPR methods and categorizing them according to the features used in each stage and compares them for its pros, cons, accuracy, and processing speed. Fast extraction of license plate region based on color image segmentation was proposed by Lee and Kim. Abbas Al-ghaili, Rahman Ramli, and Alyani used vertical-edge-based car-license-plate detection method which used unwanted line elimination algorithm. R. D. Maia, V. D'angelo [4] used genetic algorithm. GA was used to manipulate the problem from the texture perspective to differentiate between text and other image types. Intensive computational demand and sensitivity to the presence of other text such as bumper stickers or model identification was its drawback. J. Xiong, S. Du, D. Gao, and Q. Shen [7] also used GA GA to search for the best fixed rectangular area having the same texture features as that of the prototype template. The drawback was used technique lacks invariability to scaling because fixed parameters have been used for the size of the plate's area.

III. Proposed Method

A. Input RGB Image

The captured image is color image keeping an account for the factor that other relevant information of the vehicle are known. RGB image has three channels.

Figure.1. Input RGB image

B. Convert RGB to Grayscale

A color space is a specification of a coordinate system and a subspace within that system where each color is represented by a single point. The argument is that in the YIQ color space the luminance (Y) represents the grayscale information while hue (I) and saturation (Q) represents the color information.

$$I = 0.2989 * R + 0.5870 * G + 0.1140 * B$$

C. Grayscale to Binary Using Dynamic Adaptive Threshold

A binary image is a digital image that has only two possible values for each pixel. Two colors used for a binary image are obtained in the previous stage is converted to binary image. This is one of the critical stages in process because of variations coming across based on temporal and spatial factors in the surrounding and plate. Binary based on Global threshold may not see through all the challenges.

Figure. 2. Grayscale image

D. Morphological Operations

Morphological image processing is a collection of non-linear operations related to the shape or morphology in an image. Dilation of A up on B is denoted by A⊕B is a set operation.

$$A \oplus B = \{z \mid (\hat{B})_z \cap A \neq \phi\} \qquad (1)$$

where B^ is the reflection of the structuring element B. Gray-scale dilation A(x, y) by B(x, y) is

$$(A \oplus B)(x, y) = \max\{A(x - x', y - y') \mid B(x', y') \mid (x', y') \in D_B\} \qquad (2)$$

where D_B is the domain of the structuring element B and A(x, y) is assumed to be −∞ outside the domain of the image. Structural elements used for grayscale dilation is equivalent to a local-maximum operator:

$$(A \oplus B)(x, y) = \max\{A(x - x', y - y') \mid (x', y') \in D_B\} \qquad (3)$$

The binary erosion of A by B, denoted $A \ominus B$, is defined as the set operation

$$A \ominus B = \{z \mid (B)_z \subseteq A\} \qquad (4)$$

Pixels locations are *z*, the structuring element are translated to location *z* overlaps only with foreground pixels.

$$(A \ominus B)(x, y) = \min\{A(x + x', y + y') - B(x', y') \mid (x', y') \in D_B \qquad (5)$$

where D_B denotes domain of the structuring element *B* and *A*(*x*, *y*) is assumed to be +∞ outside the domain of the image.

$$(A \ominus B)(x, y) = \max\{A(x - x', y - y') \mid (x', y') \in D_B\} \qquad (6)$$

E. *Connected Component Analysis*

Connected components labeling scans an image and groups its *pixels* into components based on pixel connectivity. After all the groups have found, each pixel is labeled with a gray level or any color according to the component it was assigned to. As a final step, a second scan is made along the image in which each label is replaced by the label assigned to its equivalence classes. Extracting and labeling of various disjoint and connected components in an image is central to many automated image analysis applications. Every objects which are within the binary image are found out using an eight point connected component analysis. Array with N objects is the output from stage.

F. *Size Filtering*

The objects extracted from the connected component analysis stage are filtered on the basis of their widths Wobj and heights Hobj such that the dimensions of the LP symbols lie between their respective thresholds as follows: Wmin ⩽ Wobj ⩽ Wmax and Hmin ⩽ Hobj ⩽ Hmax.

IV. GENETIC ALGORITHM

Concerning to its internal functions of a genetic algorithm is an iterative procedure which usually operates on a population of constant size and is basically executed in the following way: An initial population of individuals (also called as "solution candidate" or "chromosomes") is generated randomly or heuristically. In each iteration the individuals of the current population are evaluated and assigned a certain fitness value. To form a new population individuals are first selected (usually with a probability proportional to their relative fitness value), and then produce offspring candidates which in turn form the next generation of parents. This ensures that the number of times an individual is chosen is approximately proportional to its relative performance in the population. Producing new solution candidate's genetic algorithms use two operators called crossover and mutation.

Crossover is the primary genetic operator in which two operators are taken as individuals, called parents, and produces one or two new more individuals, called offspring, by combining parts of the parents. The operator works by swapping substrings before and after a randomly selected crossover point. Mutation is essentially an arbitrary modification which helps to prevent premature convergence by randomly sampling new points in the search space. Bit strings mutation is applied by simply flipping bits randomly in a string with a certain probability called mutation rate. Genetic algorithms are stochastic iterative algorithms which cannot guarantee convergence; termination is hereby commonly triggered by reaching a maximum number of generations or by finding an acceptable solution or more sophisticated termination criteria indicating premature convergence. A special and quite restricted genetic algorithm variant that has represents the basis for theoretical considerations for a long period of time. Genetic algorithm with binary representation operating with generational replacement a population of constant size and the following genetic operators: roulette wheel selection single The formulation of the GA phase to resolve the 2-D compound object detection problem will be introduced in detail, indicating the encoding process, initial population, fitness function, selection method, mutation and crossover operator design and parameters setting. During each iteration step also called as "generation" the individuals of the current population are evaluated and assigned a certain fitness value. To form a new population individuals are first selected and then produce offspring candidates which in turn form the next generation of parents. This ensures that the number of times an individual is chosen is approximately proportional to its relative performance in the population. For the creation of new solution candidate's genetic algorithms use two operators, mainly crossover and mutation.

A. *Chromosome Encoding*

Encoding of a compound object such as the LP is accomplished based on the constituting objects inside the plate. The next step after plate detection is to recognize the license number; symbols identifying the plate number should be included as a minimum.

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

B. *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. First we will demonstrate how the geometric relationships between the objects inside a compound object are represented, then follows a of parameter adaption in the case of various LP detection layouts. For any two objects, two types of geometrical relationships are used that can be defined as follows.

- Position relationship: This is represented by the relative distances between the bounding boxes of the two objects in the *X* and *Y* directions.
- Size relationship: This represented as the relative differences in their bounding boxes' heights and widths.

Gene number (i)	1	2	3	4	5	6	7
Object index(j)	10	5	1	8	17	21	55

Figure.3. Chromosome

$$RX_{2,1} = X_2 - X_1/H \quad (7)$$

$$RY_{2,1} = Y_2 - Y_1/H \quad (8)$$

Size relationship is given by the following formulas:

$$RH_{2,1} = H_2 - H_1/H_1 \quad (9)$$

$$RW_{2,1} = W_2 - W_1/H_1 \quad (10)$$

The above representation, although preserves the geometric relationships between the rectangles bounding the objects, it may not represent the shape of the objects because they are unknown in the case of an unknown plate. The aspect ratio for fixed width fonts can be added for the first object as follows:

$$AS_1 = W_1/H_1 \qquad (11)$$

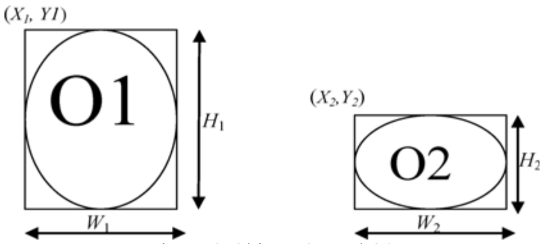

Figure.4. Objects O1 and O2

Considering the distance between the prototype chromosome *p*, corresponding to the input geometric relationship matrix, any chromosome *k*, and five distance values can be defined as follows:

$$\Delta RX_{k,p} = {}^{L-1}\sum_{j-1} |(RX_{j+1,j})_k - RX_{j+1,j})_p| \qquad (12)$$

$$\Delta RY_{k,p} = {}^{L-1}\sum_{j-1} |(RY_{j+1,j})_k - RY_{j+1,j})_p| \qquad (13)$$

$$\Delta RW_{k,p} = {}^{L-1}\sum_{j-1} |(RW_{j+1,j})_k - W)_p| \qquad (14)$$

$$\Delta RH_{k,p} = {}^{L-1}\sum_{j-1} |(RH_{j+1,j})_k - RH_{j+1,j})_p| \qquad (15)$$

$$\Delta AS_{k,p} = |AS_k - AS_p| \qquad (16)$$

The distance values will be considered the objective distance functions in this genetic algorithm problem, which could be minimized. Combining the five objective distance functions into one global objective distance function ODk,p which is used to represents the distance between any chromosome k and the prototype chromosome p is performed through the following formula:

$$OD_{k,p} = wx\Delta RX_{k,p} + wy\Delta RY_{k,p} + wh\Delta RH_{k,p} + ww\Delta RW_{k,p} + was\Delta AS_{k,p} \qquad (17)$$

where wx,wy,wh,ww and was are weighting parameters that should be given values according to the problem under consideration. The fitness is a function that should be maximized and fitness of chromosome k (Fitk) can be related to the global objective distance function as follows:

$$Fit_k = -OD_{k,p} \qquad (18)$$

TABLE 1. GRM MATRIX REPRESENTATION SAMPLE

J	1	2	3	4	5	6
$RX_{j,j+1}$	0.45	0.45	0.45	0.56	1	1
$RY_{j,j+1}$	0	0	0	0.1	0	0
$RH_{j,j+1}$	0	0	0	-0.06	0	0
$RW_{j,j1}$	0	0	0	-0.4	0	0

The previous formulation can be used for the representation of a compound object consisting of a group of smaller objects and can be used to locate the compound object in an image given that its GRM values are nearly fixed. The formulated method has the advantage of overcoming scaling effect. It also overcomes orientation variability either by aligning the compound objects to a certain direction line or by taking projection parameters into account in the original formulation. Detection of plates having different orientations has been achieved as will be shown in the results section due to the flexible range of accepted fitness (or objective distance) values.

$$OD_{k,p} = \Delta RX_{k,p} + 4\Delta RY_{k,p} + 4\Delta RH_{k,p} \qquad (19)$$

It should be recorded here that the selection of the weighting parameters affects and guides the genetic search space during the production of new generations and hence affects both the speed and accuracy of the overall system. The formula for the fitness of a chromosome k is given as follows:

$$Fit_k = -\Delta RX_{k,p} - 4\Delta RY_{k,p} - 4\Delta RH_{k,p} \qquad (20)$$

C. Selection method

The stochastic universal sampling (SUS) method is implemented for the selection of offspring in the new generation. In the SUS method each individual is mapped to continuous segments of line which is equal in size to its fitness as in roulette-wheel selection. A number of similarly spread out pointers are placed over the line depending on the ratio of individuals to be selected. In the introduced system, individuals of 90% of the population size (0.9 Z) are particular to be showing to mutation and crossover operators.

D. Mutation Operators

Mutation is needed because successive removal of the less fit members in genetic iterations can eliminate some aspects of genetic material forever. We have implemented two types of the interchangeable mutation operators.

- Substitution Operator: These types of operators where a random position in the chromosome is nominated and the corresponding allele is changed by a new random object from the M available objects.
- Swap Operator: The operator does reciprocal exchange mutation which selects couple of genes randomly and swaps them.

E. Crossover Operator

There are many methods used to implement the crossover operator. Single-point crossover, three-parent crossover, two-point crossover, n-point crossover, uniform crossover, alternating crossover are different types of crossover operators. An alternative solution is to design a suitable crossover operator that insures enhancement of the generated offspring.

F. Stopping Criteria

Stopping criteria of the genetic algorithm are set as follows:

- The best chromosome’s objective distance (OD) is less than 5.
- The average objective distance is not improved for six successive generations.

V. RESULT AND ANALYSIS

Experiments were carried out for various camera-to-object relative positions in different lighting conditions. Results are summarized false positive (FP) means assigning incorrect locations to license plate symbols. Undoubtedly, remaining undetected cases are false negative. The detection rate is higher than we have less FP rate (0.25%). Output of our system is at the second stage of license plate recognition systems that implied error percentage will be increased after the symbol segmentation stage. The method used random samples from to adapt the system that may be considered as the training samples which are used again in the test phase.

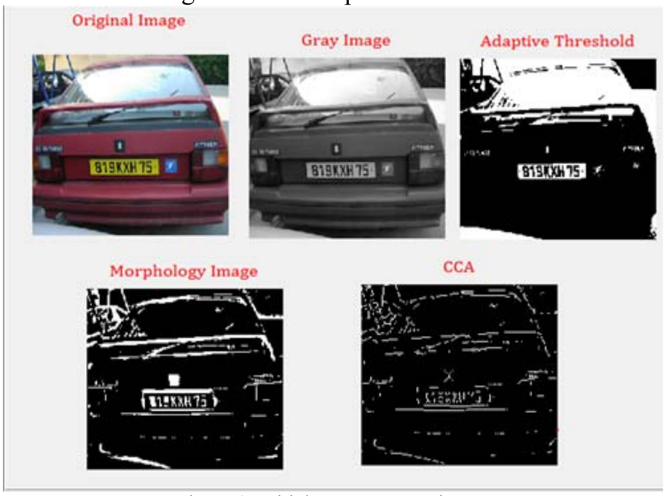

Figure 3. Initial Image processing

Scaling will not affect the results if done on the same dataset as far as the candidate symbols lie inside the definite ranges in the size filtering stage. Sample images reveal the robustness and distinction of the proposed approach. The real number below each image indicates the objective distance value giving the input prototype geometry relationship matrix for each experiment. Without code optimization and a system working on a 2.6 GHZ with 2 GB RAM, on a mean of scale, 0.12 s was taken to locate the license plate symbols for low resolution images (640×480) and 0.34 s for high resolution images.

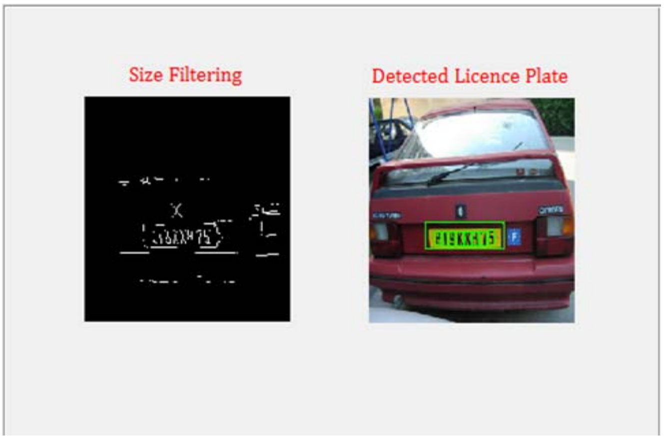

Figure 4. Detection of license plate

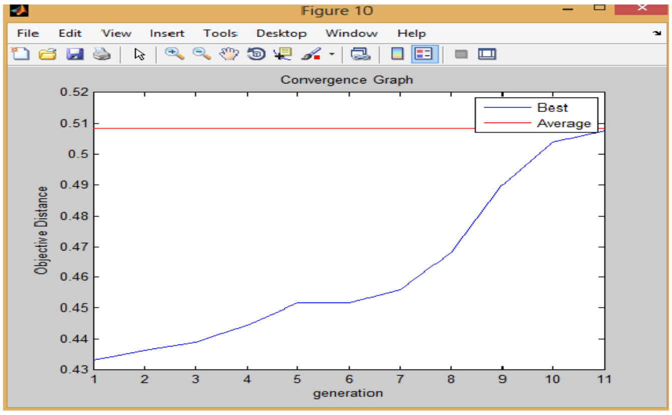

Figure 6. Convergence graph

Considering the genetic phase's speed, great enhancement has been achieved. Future research could look for clustering objects according to their sizes and positions prior to be supplied to the genetic phase to allow for the identification of multiple plates and at the same time to increase the system speed. System can be used in parking management systems, and in the detection of license plates in pictures taken in emergent circumstances that might not allow change of the position and orientation of the camera with respect to the vehicle. Another important fact that should be recorded here is that t many types of local adaptive thresh-holding methods have been tried, none of them gave 0% error rate but after introducing the skipping part of the genetic algorithm phase the error percentage due to binary images has been minimized. Local adaptive thresh-holding was used in many previous researches, but integrating it with CCA and the skipping method gives the technique distinction among other techniques. Instead of increasing the computation time the skipping method in the genetic phase reduces human involvement factor in the case of system failure in the detection of some license plates.

A. How to Meet the Challenges?

To meet the challenges in the real time conditions our research adopts three techniques in camera technology. They are as follows:

- Fast shutter speed
- Light bending technology
- Infrared illuminator

Figure 5. Motion blur reduction by fast shutter speed camera

Figure 6. Light bending technologies

Figure 7 Infrared illuminator

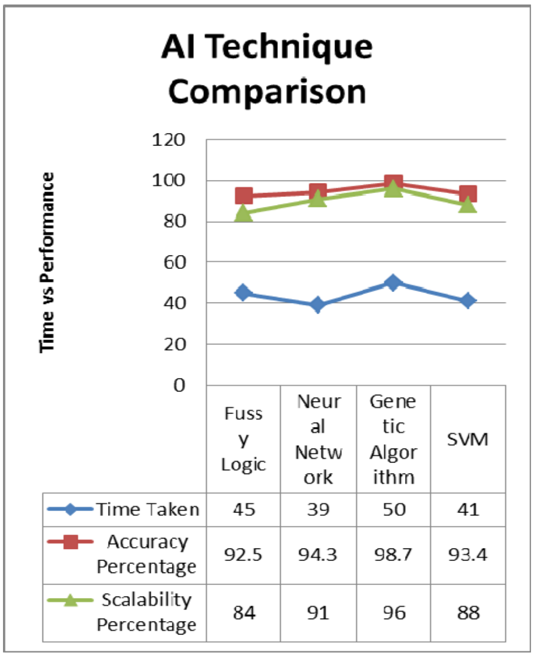

Figure 8. AI techniques comparison

The figure above shows the comparison of artificial intelligence techniques used in the license plate detection problem and their comparison. Results of the comparison prove that even though the genetic algorithm takes a bit few milliseconds to give the result, the accuracy of the recognition is never compromised. In most of the license plate recognition cases accuracy is given more priory than the time taken.

VI. Conclusion And Future Work

A new genetic-based prototype system for localizing compound objects in the images was introduced and tested in the localization of license plate symbols. The results were encouraging and a new approach for solving the license plate identification problem relying mainly on the geometrical layout of the license plate symbols was experimentally proved. The independency used on color and the adaptive threshold for binary conversion, the proposed system possessed high resistance to changes in illumination temporarily or spatially through the plate's area. Our experiments proved that even though leaving few features in the compound object representation, because of the variable nature of the objects such as the aspect ratios and the relative widths, high percentage success rate was able to achieve with the aid of the adaptability aspect of the GAs. Another important achievement is overcoming most of the problems raised when the connected component analysis technique was used by allowing the genetic algorithm to skip gradually as well as randomly one or more than one symbols to reach to an acceptable value of the objective distance. An enhancement in the performance of the developed genetic algorithm was achieved by applying USPS operators, caused the convergence speed to increase greatly in the whole system. A new research dimension for genetic algorithms was opened to allow for the detection of multiple plates and also different styles in image and the increase in the performance in terms of speed, memory and applying the same technique in other problem domains analogous to the license plate problem.

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