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Localization Of Multistyle License Plate Number Using Dynamic Image Processing And Genetic Algorithm

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Abstract--Genetic Algorithm and dynamic image processing techniques are used for localizing the license plate number in an image. Recognition of LP symbols in a picture with high immunity for changes in illumination is done using this process. The proposed system finds multistyle number plates in an image. Implementation is done using MATLAB with sample images for proving the proposed model's distinction.

Keywords--License plate detection, Genetic algorithm, CCAT

1. INTRODUCTION

The detection stage of the license plate (LP) is the most critical step in an automatic vehicle identification system. Much research has been carried out to overcome many of the problems faced in this area, but there is no general method that can be used for detecting license plates in different places or countries, because of the difference in plate style or 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. With advancement in artificial intelligence and computer science, intelligent systems such as intelligent transportation systems play more and more important role in modern society [1]. Among these systems license plate recognition is used in many applications including automatic toll payment, identification of stolen vehicles, border control, and traffic law enforcement. A license plate recognition system generally consists of three processing steps: license plate detection, character segmentation, and character recognition [2]. There are many factors to be taken into account when developing license plate detection method. License plate standards vary from country to country. Images can be captured in different illumination conditions and may contain other objects such as buildings, people, trees, fences etc. Also the number of vehicles and the distance between the vehicle and the camera can vary [3]. This makes license plate detection to be the most important and challenging step. For many years, moving object detection and location is a focus in the field of image processing, and its key technology is feature extraction and description. The most frequently used features are texture, geometrical configuration and gray feature [4]. However, these features are often subject to different environment such as view point and distance. The MSER feature is affine-invariant to scale transformation, rotation transformation and transformation of the view-point, so it has great advantages over the common features in robustness, repetition rate, discrimination [5].

figure 1. car license plate

II. LITERATURE REVIEW

The edge part is obtained from the use of Difference of Gaussian operation followed by Sobel vertical edge mask. Prior to that, gamma correction is applied to increase the detection of edges. We then apply morphological operations to get the plate region candidates. Using these regions, together with the edge image, we calculate geometrical features of these regions and use rule-based classifier to correctly identify the true plate region. license plate recognition using a three layer fuzzy neural network. In the first stage the plate is detected inside the digital image using rectangular perimeter detection and the finding of a pattern by pattern matching, after that, the characters are extracted from the plate by means of horizontal and vertical projections. License plate detection is an important processing step in license plate recognition which has many applications in intelligent transportation systems. Vertical edges and edge density features are utilized to find candidate regions. Sequential Constructive crossover (SCX), for a genetic algorithm that generates high quality solutions to the Traveling Salesman Problem (TSP). The sequential constructive crossover operator constructs an offspring from a pair of parents using better edges on the basis of their values that may be present in the parents' structure maintaining the sequence of nodes in the parent chromosomes. The efficiency of the SCX is compared as against some existing crossover operators; namely, edge recombination crossover (ERX) and generalized N-point crossover (GNX) for some benchmark TSPLIB instances [6].

III. ALGORITHM

In a genetic algorithm, a population of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem is evolved toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered; traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible.

The evolution usually starts from a population of randomly generated individuals, and is an iterative process, with the population in each iteration called a generation. In each generation, the fitness of every individual in the population is evaluated; the fitness is usually the value of the objective function in the optimization problem being solved. The more fit individuals are stochastically selected from the current population, and each individual's genome is modified (recombined and possibly randomly mutated) to form a new generation. The new generation of candidate solutions is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population.

A. Genetic operators

The next step is to generate a second generation population of solutions from those selected through a combination of genetic operators: crossover (also called recombination), and mutation.

For each new solution to be produced, a pair of "parent" solutions is selected for breeding from the pool selected previously. By producing a "child" solution using the above methods of crossover and mutation, a new solution is created which typically shares many of the characteristics of its "parents". New parents are selected for each new child, and the process continues until a new population of solutions of appropriate size is generated. Although reproduction methods that are based on the use of two parents are more "biology inspired", some research suggests that more than two "parents" generate higher quality chromosomes.

gene number (i) :	1	2	3	4	5	6	7
object index (j)	3	1	5	7	11	2	15

Figure 2: Chromosome of numbers

1. 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.

2.Size relationship: The size relationship will be represented as the relative differences in their bounding boxes' heights and widths. In the above relationships, relativity is achieved by dividing on the height or width of the first object depending on which is more stable for practical reasons although it is logically to divide differences in heights on height and differences in widths on width to compensate for scale changes in the general case.

For most LPs, the heights of symbols are almost equal for both digits and letters while some symbols have different widths than others. Hence, normalized relationships between any two objects can be based on the height of the first object.

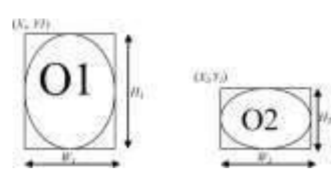

Figure 3. layout of object

The position relationship is defined in the two directions by the following formulas:

$RX_{2,1} = (X_2 - X_1)/H_1$ (1)

$RY_{2,1} = (Y_2 - Y_1)/H_1$ (2)

The size relationship is defined by the following formulas:

$RH_{2,1} = (H_2 - H_1)/H_1$ (3)

$RW_{2,1} = (W_2 - W_1)/H_1$ (4)

4. Implementation

The genetic algorithm is implemented using MAT LAB. Initially a input image of car is taken, which is an RGB image. To extract the numbers present in LP, the following steps are carried out.

Step 1: Binarization

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. The idea in Wellner's algorithm is that the pixel is compared with an average of neighboring pixels. Specifically, an approximate moving average of the last S pixels seen is calculated while traversing the image. Whereas it should be in the range

$0.1 < T < 0.2$

Step 2: Noise objects elimination

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.

Step 3: Encoding and Recognition

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. The simplest algorithm represents each chromosome as a bit string. Typically, numeric parameters can be represented by integers, though it is possible to use floating point representations. The floating point representation is natural to evolution strategies and evolutionary programming.

Step 4: Fitness function

The proposed fitness is selected as the inverse of the calculated objective distance between the prototype chromosome and the current chromosome. Geometric relationships between the objects inside a compound object are represented, followed by a discussion of parameter adaption in the case of various LP detection layouts. Objective distance (OD) is the best chromosome's less than 5. (This value is found by trial and error).

$\Delta RX_{k,p} = \quad (RXj{+}1,j)k - (RXj{+}1,j)p \mid$ (5)

$\Delta RY_{k,p} = \quad (RYj{+}1,j)k - (RYj{+}1,j)p \mid$ (6)

$\Delta RW_{k,p} = \quad (RWj{+}1,j)k - (RWj{+}1,j)p \mid$ (7)

$\Delta RH_{k,p} = \quad (RHj{+}1,j)k - (RHj{+}1,j)p \mid$ (8)

Step 5: Extraction

Feature extraction a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. This approach is useful when image sizes are large and a reduced feature representation is required to quickly complete tasks such as image matching and retrieval. 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. Individuals of ninety percent of the population size are selected to be exposed to mutation and crossover operators.

Mutation operator

Mutation is needed because successive removal of less fit members in genetic iterations may eliminate some aspects of genetic material forever.

Substitution operator

These types of operators, a random position in the chromosome are selected and the corresponding allele is changed by a new random object from the *M* available objects. As shown in Fig (4)

Swap operator

The reciprocal exchange mutation that selects two genes randomly and swaps them, as shown in Fig (4)

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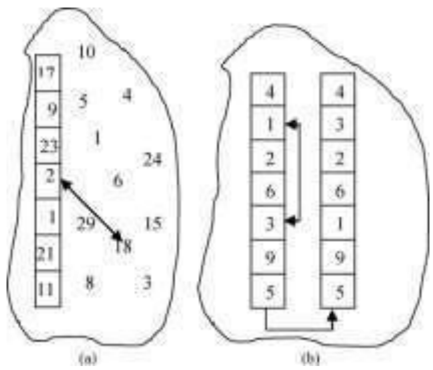

Fig 4: Example for (1) Substitution operator and (2) Swap operator

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.

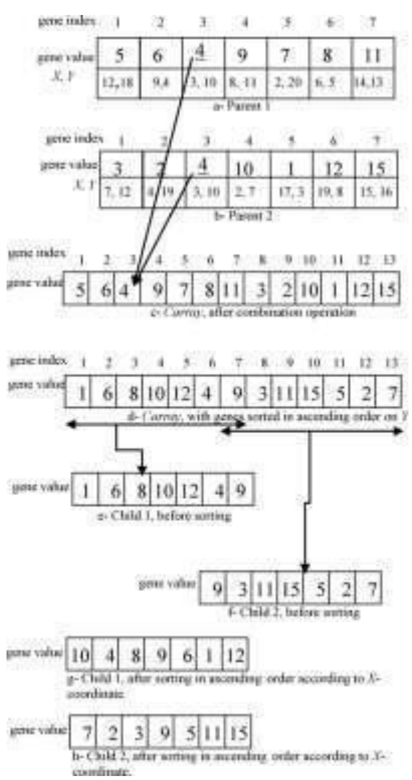

Figure 5. Example Crossover Operation

IV. Result and Conclusion

Thus the numbers on license plate from the input image is extracted using genetic algorithm as shown in Fig (6) and Fig (7)

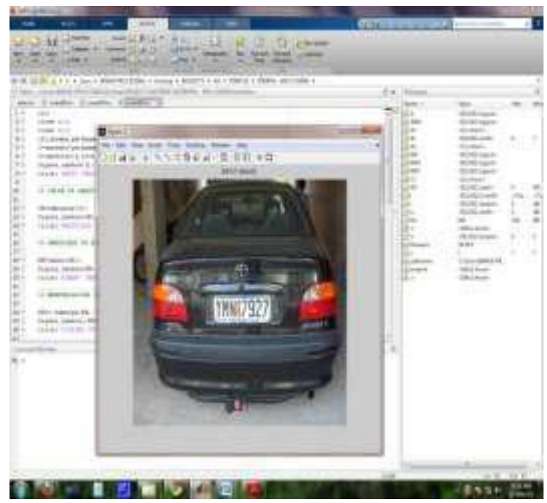

Figure 6: Input Image

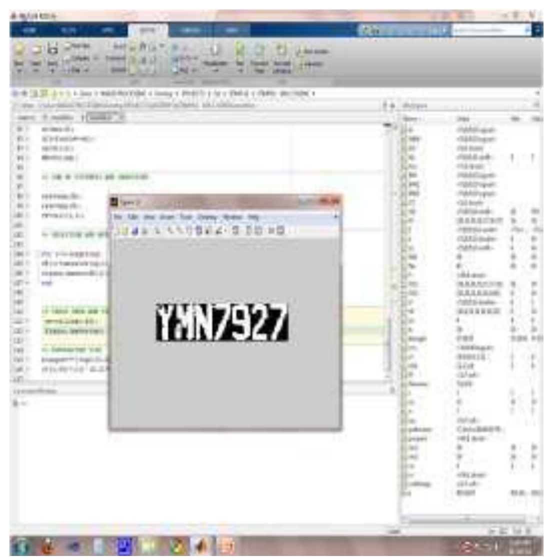

Figure 7.Numbers Extracted From License Plate

By using genetic algorithm, the detection and extraction of license plate number is much faster, and also this can be applicable in different conditions.

VI. Future scope

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In the future of this paper to allow for the detection of multiple plates and even multiple styles in the same image and to increase the performance in terms of speed and memory and to apply the same technique.

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