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A Genetic Algorithm and Artificial Neural Network-based Approach for the Machine Vision of Plate Segmentation and Character Recognition

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***Abstract*— This paper proposes a genetic-algorithm and neural network-based approach in the optimization of the process of plate segmentation and character recognition respectively in intelligent transportation systems. Upon the detection of the vehicle's plate from a captured image, it is necessary that the individual characters in the detected plate are distinguished. After the process of plate recognition, the recognized plate number can be crossed-referenced against a database to correctly identify the vehicle's owner and ultimately penalize him for the traffic rule he violated. The segmentation algorithm captures the region of each character in the detected plate using genetic algorithm. After which, each plate character image is mapped against its corresponding sample character image. This is done by feeding sample character images into an artificial neural network and training the network.**

***Index Terms*— genetic algorithm, artificial neural network, plate recognition, character recognition, plate segmentation, machine vision**

I. Introduction

Traffic violation has been a rampant problem in the Philippine roads. By giving the appropriate penalties to the violators, the number of traffic problems associated to the violations is expected to decrease. Thus, the need for an intelligent transportation system that can automatically detect such violations to capture the violators arises. An important subsystem of the mentioned process involves the recognition of the plate number of the vehicle owner. A number of studies have proposed several methodologies to implement this.

Moghassemi and Broumandnia used Zernike and wavelet moments features to recognize Iranian license plate characters. Their algorithm proved to be robust under any complicated environment due to their wavelet moments features including rotation and scale invariant property [1]. A study made by Bolotova, Druki and Spitsyn proposed the hierarchical temporal memory model for character recognition which can be used for distorted text recognition by training the algorithm using sloping characters. Thus, the problem of recognizing plate characters when CCTVs capture license plates at different angles is minimized [2]. Averaging of White Pixels in Objects (AWPO) and method of the Euclidian distance and template matching were used for plate segmentation and character recognition, respectively by Salahshoor, Broumandnia and Rastgarpour which proved to be robust under different image conditions [3]. In a paper presented by Kasaei and Kasaei, they used a morphology-based technique for the plate localization process while a template-matching scheme was used to recognize the plate characters [4].

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Artificial neural networks have also been widely used in the character recognition process. In a research done by Wu, Xinhan, Min and Yexin, neural networks is implemented with improved recognition rates because the plate-type was previously identified by using another neural network classification algorithm using the pixel colors of the plate area [5]. License plate recognition was not only used for the apprehension of traffic violators but also for other purposes such as automatic parking systems. A study by Sirithinaphong and Chamnongthai used supervised backpropagation neural network with four layers for such applications. Characters-pattern recognition was implemented using the aforementioned neural network model [6]. Against backpropagation neural networks, it was learned in Wang's study that Radial Basis Function Neural Networks (RBFNN) can work more efficiently by reducing the training and recognition time and the error rate as well as the complexity of the architecture [7]. The neural network as a tool for plate recognition was also improved in a study made by Lee and Hung by using a scanning window and one-dimensional periodic wavelet transform and selecting frequencies with low coefficients [8]. Probabilistic neural network was employed by Chen, Chen, Wu, Hu and Tang for character recognition upon segmentation using their proposed weighted-binarization method [9].

Other studies focused on the other steps of the whole plate identification process to improve the character recognition accuracy. Prabhakar and Anupama's thesis presented another method of plate recognition by giving emphasis on the plate segmentation process as the character recognition's accuracy depends largely on the accuracy of the former [10]. In Zheng, He, Samali and Yang's paper, they obtained higher recognition accuracy by removing license plate boundaries upon detecting the plate. The character recognition itself was performed by an Optical Character Recognition (OCR) software [11]. The antinoise ability of the extension theory was used and applied by Pai, Huang, Kuo and Kuo to develop a license plate recognition system with increased recognition accuracy [12].

II. Genetic Algorithm

In any intelligent system, for instance neural networks, learning becomes an optimization process wherein the error is minimized. However, in recent advancements, problems require an algorithm to become adaptive, or it is dynamically changing along with its environment. Biological evolution, which is performed by living things to adapt to their environment, became an interesting solution to such problems. Genetic algorithm, which involves an evolution process, provided a new method for optimization that determines the parameters that will produce the minimum or maximum of a function. It evaluates the function at random points and converges at the local maxima or minima of the function within the domain, which becomes the solution [13].

In genetic algorithms, biological terms used in evolution are also used. A chromosome denotes a possible solution to the function. Often, it is represented by a bitstream. A gene is a parameter that can define a chromosome, and can be denoted either as a single bit or consecutive bits within the chromosome whereas an allele is a single bit. The crossover process involves the exchange of genetic material or bits between chromosomes. In mutation, bits are flipped at a randomly chosen locus [14].

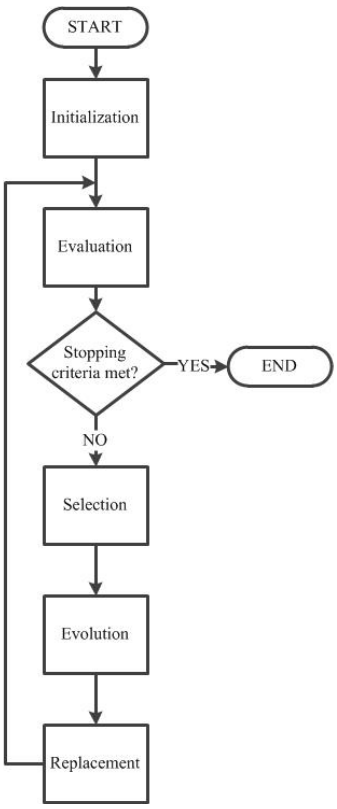


Fig. 1. Genetic Algorithm Flowchart

Shown in Figure 1 is the flowchart for the genetic algorithm process. The initialization process involves the creation of a random population of chromosomes, which are candidate solutions to the problem or the function. During evaluation, the fitness of a chromosome is computed using the fitness function. The fitter the chromosome, the better option it is as a solution. Selection uses the idea of the survival-of-the-fittest wherein solutions with higher fitness values are preferred over those with lower fitness values. Different methods such as roulette-wheel selection, stochastic universal selection, ranking selection and tournament selection can be used for the selection process. Evolution can be performed by either recombination or mutation. During recombination, two or more parent chromosomes combine their traits to create offspring chromosomes, which can possibly be better than them. In mutation, however, only a single chromosome is involved in the creation of a new chromosome, wherein it modifies some of its own traits. In the replacement process, the offspring population replaces the original parent population which can be done by elitist replacement, generation-wise replacement and steady-state replacement methods. The whole process is repeated until a single solution satisfies the stopping error criterion [15].

Genetic algorithms have been implemented in a variety of applications, including but not limited to optimization, automatic programming, machine learning, economic models, immune system models, ecological models and social system models [16]. In this paper however, genetic algorithm will be the emphasized as a tool for optimization and machine learning.

III. Methodology

The flowchart in Figure 2 shows how the overall traffic violation apprehension process works. The captured image from a stationed CCTV will be evaluated to detect any traffic violators. If at least one is detected, the vehicle is identified and the plate number area is captured. This paper focuses on the recognition of the characters in the plate to correctly identify the owner of the vehicle, thus apprehending the violator.

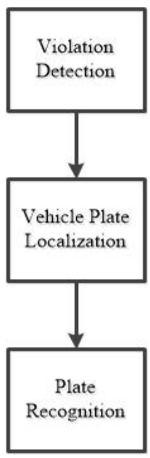


Fig. 2. Traffic Violation Apprehension Flowchart

The process of plate recognition starts by converting the plate image into a black-and-white image which effectively turns the plate image into a matrix of bits, 1 corresponding to white while 0 represents black pixels. The segmentation process then takes place which involves capturing the area of each individual character in the plate which is performed and optimized via genetic algorithm. By segmenting the plate into individual characters, the process of character recognition is performed one character at a time. To recognize the character, an artificial neural network was created to map sample character images to the desired output. After training the artificial neural network, each character is divided into nine equal parts which is then fed to the network.

A. Fitness Function Evaluation

The fitness function used to find the location of each character in the detected plate, or the segmentation process, is shown in the equation

$$y = \frac{1}{h * w} \sum_{k=1}^{w} \sum_{i=1}^{h} I$$

where y is the ratio of the white pixels to the total number of image pixels, I is the image matrix in black-and-white, h is the number of rows of the image matrix and w is the number of columns of the same image matrix.

In the fitness function, the ratio of the white pixels over the whole pixel area of the plate image will correspond to the fitness value of the chromosomes. In the algorithm, the original population and their offspring population will continue to evolve and be evaluated until a chromosome satisfies the stopping criterion. For the segmentation purposes however, instead of converging into only one solution, seven chromosomes are instead identified as the best fits which correspond to the seven characters in the plate image.

B. Chromosome Reproduction and Evolution

The initial population of chromosomes, each of which is 20-bits wide, is generated randomly. For succeeding iterations of the algorithm, a new set of chromosomes are reproduced by older chromosomes through the crossover process. This evolution process involves two parent chromosomes that create an offspring by combining their bits. In other words, some bits of one chromosome are replaced by the bits of another chromosome. This process creates a new and supposedly better chromosome by generating an offspring which have the characteristics or genes of each parent desired for the optimum solution.

C. Stopping Criteria

The stopping criteria will limit the iteration or reproduction of further chromosomes when a chromosome has already been evaluated to satisfy the stopping criterion. In this study, the algorithm stops when it evaluates a chromosome whose white-to-whole-image pixel ratio is at least 0.4. Moreover, it was incorporated in the segmentation process that the border bits (the first and last row and column vectors in the image matrix) is 1. This minimum requirement ensures that the victorious chromosomes of the algorithm will display the individual characters of the plate image.

D. Artificial Neural Network of Character Recognition

Shown in Figure 3 are some of the sample character images. These sample images follow the standard font as well as the background color of license plate numbers in the Philippines. The data from these sample images are the ones that will be fed to the artificial neural network as training data.

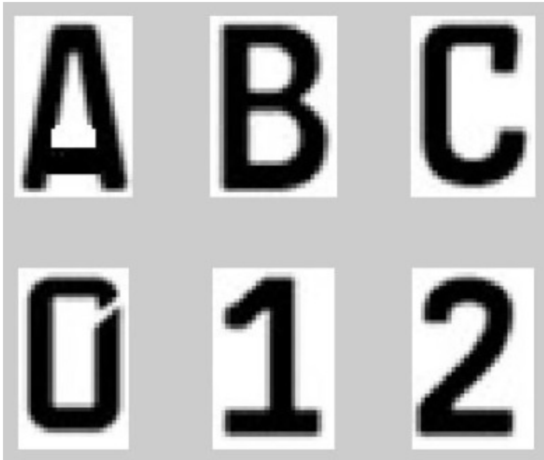
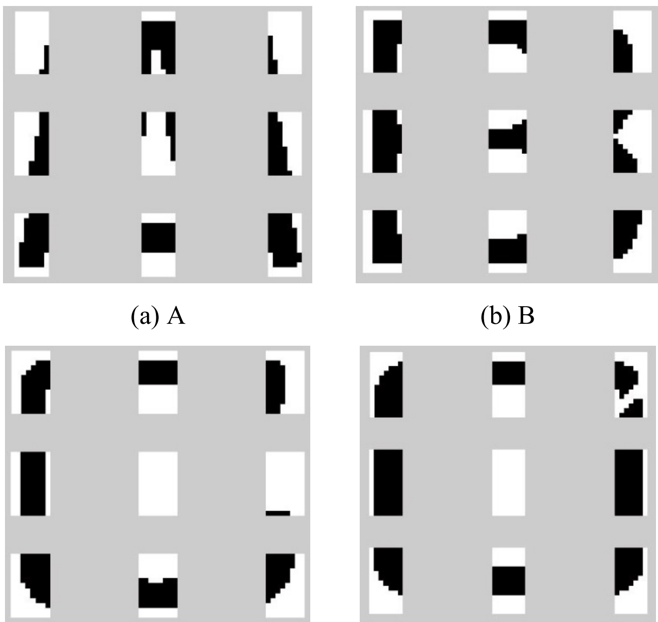


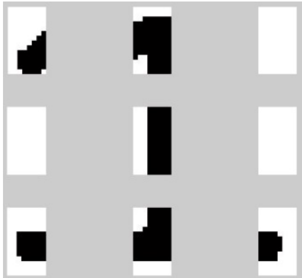
Fig. 3. Sample Character Images (A, B, C, 0, 1, 2)

Figure 4 shows how the previously shown sample character images are sectioned into nine blocks. Sectioning into nine blocks was done to ensure that the plate character image is correctly identified since the criteria for mapping will again be the ratio of white-to-whole-image pixel. By sectioning it to nine blocks, each block's pixel ratio will be calculated and be fed to the neural network. The neural network's task is to map these nine blocks into a unique character. This minimizes the chances of a character image being mapped into a wrong character because of multiple mapping instances.



(a) A (b) B

(c) C (d) 0



(e) 1

(f) 2

Fig. 4. Sectioned Sample Character Images

IV. Experiment Results

The outputs of the plate recognition algorithm are the identified characters in the plate image via the aforementioned methods. Shown in Figure 5 is a sample plate image.

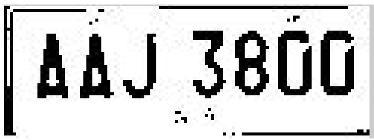


Fig. 5. Sample Plate Image

A. Plate Segmentation

The following images are extracted upon subjecting the sample plate image to the plate segmentation algorithm. As seen, seven individual images corresponding to each character of the plate were displayed. It should be noted that the order of appearance of the characters is crucial because different combinations of the characters can lead to multiple plate numbers being identified, which defeats the purpose of narrowing down and searching for the owner of the violating vehicle.

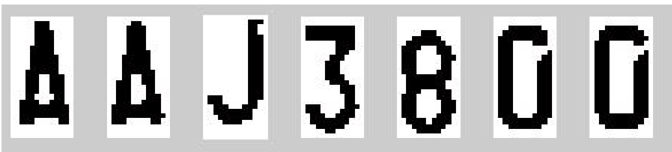
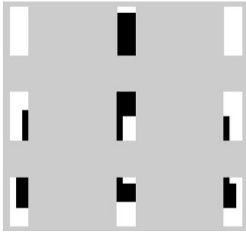


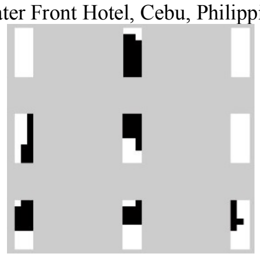
Fig. 6. Segmented Plate Image into Individual Characters (A, A, J, 3, 8, 0, 0)

B. Character Segmentation

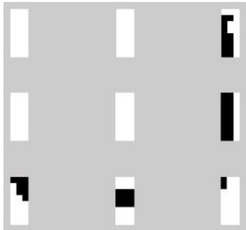
The character recognition algorithm was performed to the individual character images acquired from the segmentation process. The following images are the result of sectioning the individual images into nine blocks in the same way the sample character images that were fed to the neural network were sectioned.



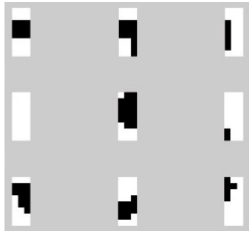
(a) 1st Plate Character



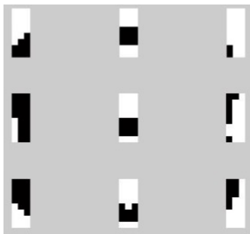
(b) 2nd Plate Character



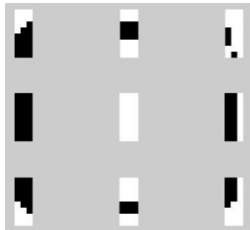
(c) 3rd Plate Character



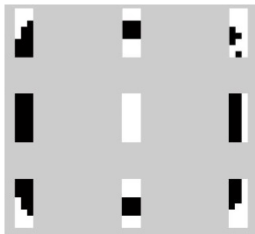
(d) 4th Plate Character



(e) 5th Plate Character



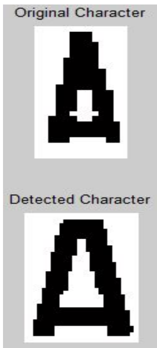
(f) 6th Plate Character



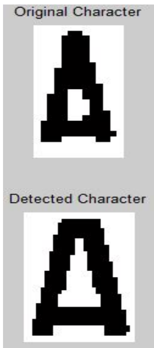
(g) 7th Plate Character

Fig. 7. Sectioned Plate Character Images

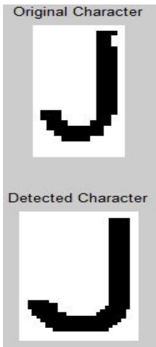
Upon training the neural network with the sample character images and feeding the images from the segmentation process, the following output images were obtained which mapped the plate character image to its corresponding recognized sample character image. Figure 8 shows the mapped character for each plate character.



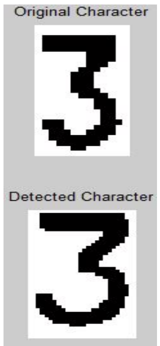
(a) 1st Plate Character



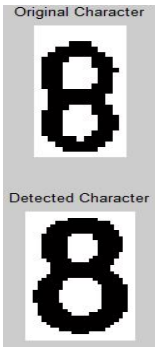
(b) 2nd Plate Character



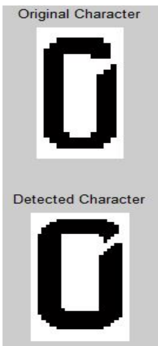
(c) 3rd Plate Character



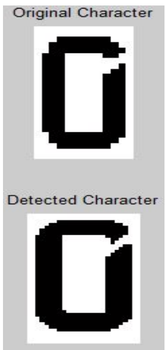
(d) 4th Plate Character



(e) 5th Plate Character



(f) 6th Plate Character



(g) 7th Plate Character

Fig. 8. Character Mapping

V. DISCUSSION AND ANALYSIS OF RESULTS

As observed from the outputs of the segmentation and recognition processes, the algorithm was able to recognize the plate number of the license plate image. With an average program run time of 2.416 s for the segmentation and individual character recognition, the whole program ran for a total of 16.913 s. Figure 9 shows a plot of the run time of the algorithm for each character recognized.

Although the plate character images are not exactly the same as the sample character images that were used as training data, the characters were mapped correctly.

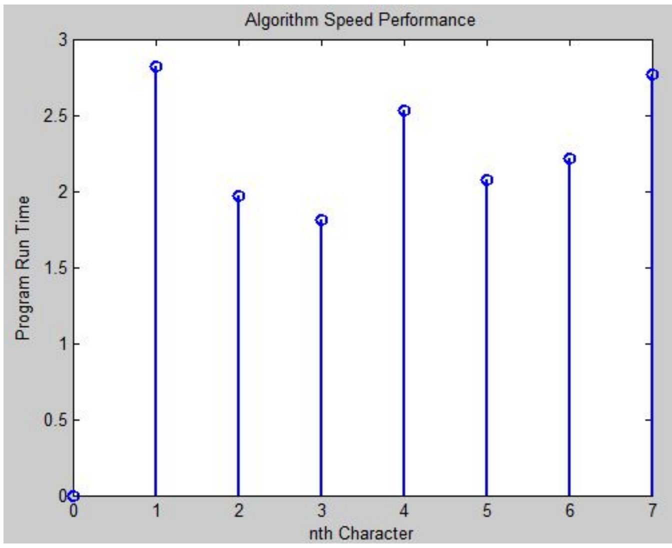


Fig. 9. Algorithm Speed Performance

VI. CONCLUSIONS AND RECOMMENDATIONS

The designed algorithm performed effectively in recognizing the characters in a license plate image. The genetic algorithm accurately identified the location of each character in the plate image which efficaciously segmented the plate into its seven characters. Even though each plate character image after segmentation was smaller in pixel size than the sample character images that were used as training data, the plate character images were correctly mapped to the sample character image. Therefore, the neural network was able to learn the nonlinear relationship between the pixel ratios for each of the nine blocks and a unique character.

Recommendations for future similar studies include taking into consideration the different environmental conditions when the plate images are taken from the CCTV. For instance, different lighting when the plate image is taken at night will greatly affect the white-to-whole-image pixel ratio of each character, hence affecting the fitness value of the correct chromosomes. Moreover, it is inevitable that some plate images will be taken at different angles which could cause distorted character images that cannot be easily recognized by the algorithm. Thus, adjustments in the algorithm should be made. Lastly, image normalization and enhancement before the character recognition process could be applied first to view the plate image more clearly since some plate images might be too blurry.

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