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Modified Genetic Algorithm Parameters to Improve Online Character Recognition

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Authors' contributions

This work was carried out in collaboration between all authors. All authors read and approved the final manuscript.

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ABSTRACT

Online character recognition is characterized with feature extraction and classification parameters that make recognition accuracy non-trivial task. Failure of existing optimization techniques to yield an acceptable solution to solve poor feature selection and slow convergence time provokes the idea for some stochastic algorithms. In this paper, a feature reduction technique that apply the power of genetic algorithm was modified using fitness function and genetic operators to minimize the aforementioned drawbacks. Two classifiers (C1 and C2) were then formulated from the integration of modified genetic algorithm (MGA) into an existing Modified Optical Backpropagation (MOBP) learning algorithm. The performance of C2 on generation gaps was further evaluated using convergence time and recognition accuracy. The research evaluation showed that C2 assumed average convergence times of 130.30, 211.69, 199.23 and 243.00 milliseconds with generation gaps of 0.1, 0.3, 0.5 and 0.7. This implies that generation gap variation had a positive effect on the network performance. Further evaluation showed that C2 assumed average recognition accuracies at 0.7 is 98.1% and 99.4% at Ggap 0.1 respectively.

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Keywords: Character recognition; genetic algorithm; feature extraction; feature selection; genetic operators and generation gap.

1. INTRODUCTION

Genetic algorithm (GA) is one of the widely used biological evolution technique for global optimization that mimic the principle of natural genetics and natural selection. GA is an iterative algorithm based on many generations of probable solutions, among selection schemes authorization the removal of bad solutions and the reproduction of good ones that can be modified [1,2]. Character recognition (CR) refers to the electronic conversion of images of handwritten or printed text into machine-editable text. However, most existing classifiers used in recognizing online characters suffer from dynamic of poor feature selection and slow convergence which affect training time and recognition accuracy [3,4]. Online character recognition constitutes a serious challenges: the complexity of noise from data, variations in character styles and mood of the writers make it difficult [5]. Adequate modeling of online character recognition mostly depends on the choice of a certain feature selection and classification procedures. Some conventional optimization methods cannot overcome these limitation, genetic algorithm is introduced as a good alternative optimization methods for solving such problems [6]. GAs popularity, like its global perspective, wide spread applicability, inherent parallelism and noise tolerance make its suitable in various search and optimization problems and character recognition accuracy [7]. However, the effectiveness of a certain optimization technique can be evaluated by the recognition accuracy achieved and the convergence time needed. Feature selection algorithm is to reduce the number of features extracted to improve classification task performance. Different feature selection algorithms are used, which include Principal component analysis, Correlation-based feature selection, Discrete wavelet transform, Linear discriminant analysis, Gabor filters and many others. In this paper MGA was used to find the optimal feature subset. The reasons for performing feature selection as stated by [8,9] was to reduce computational time, improving data understanding and better classification performance. The generation gap is the proportion of chromosomes in the population which are replaced in each generation. It is a genetic algorithm parameter used for high performance solution and greedier because it always uses the best individual of population for generating offspring [10]. Hence, the objective of the paper is to determine how significant the effect of generation gap as a sensitive genetic algorithm parameter towards recognition accuracy and convergence time. The power of genetic algorithm parameter is used to overcome the drawback of spending much time for character to converge.

2. RELATED WORK

Previous work on online handwritten character recognition had shown that feature extraction process is most important factor in achieving a better recognition performance. A number of methodologies have been proposed over the years for online character recognition and some of them have outstanding performance. [11] developed a genetic based neural network model for online character recognition. This research integrated modified genetic algorithm into modified backpropagation neural network to improve the performance of online character recognition system. This paper investigated the necessity for optimization algorithms to enhance the performance of two classifiers. The recognition accuracy obtained for developed model shown a better accuracy than other classifiers. [12] developed a paper on, conversion of handwritten data into electronic data, using neural network approach and Genetic Algorithm to recognize handwritten characters. The handwritten characters were converted to graphs and was intermixed to generate new or unique styles intermediate between the styles of parent character. [13] was the first to evaluate empirically the performance of GAs with overlapping populations. He introduced the generation gap G as a parameter to the GA, and found that at low values of G the algorithm had a severe loss of alleles, which resulted in poor search performance. [14] developed English character recognition system using the hybrid of standard backpropagation and genetic algorithm for recognition of uppercase alphabets. Recognition performance was 91.1%. Furthermore, [15] presented a backpropagation network algorithm combined with genetic algorithm to achieve both accuracy and training swiftness for recognizing alphabets. [16] presented a methodology to recognize handwritten character written on the digitizing tablet. It uses different spatial and temporal features to extract features from the character and genetic algorithm was used to find an optimal subset. The overall experimental results in recognition rate was 83.1%. The main goal is to further improve the recognition accuracy and convergence time using modified genetic algorithm and MOBP at classification level.

3. MATERIALS AND METHODS

3.1 Database Acquisition and Normalization

Fig. 2 shows the block diagram of the character recognition model which consists of character acquisition, preprocessing, feature extraction and selection, and classification. The dataset was locally acquired using a pen digitizer tablet contains 50 randomly selected students of Yaba College of Technology, Yaba. Nigeria. Character information of 26 upper case (A-Z), 26 lower case (a-z) English alphabets and 10 digits (0-9) were considered making a total of 62. The students were asked to write for each character twice to allow the network learn various possible variations the characters and become adaptive in nature. All these entries are stored and served as the training dataset which was the input data that was fed into online character recognition system. The raw data collected were subjected to a number of preprocessing steps (i.e. binarization, normalization, extreme coordinate measurement and grid resizing). This is to convert the character image to binary character, removal of noise and redundancy and the output was normalized by resizing to a matrix size of 5 by 7 for feature extraction.

3.2 Experimentation of the Model

The process of features extraction were employed to extract the features from character to aid classification task. The extracted features consist of stroke information, invariant moments, projection and zoning of the handwritten character to create a global feature vector. The output of the extracted and selected features of the handwritten character was fed into the digitization stage in order to convert the extracted features into digital form. The paper combines structural and statistical features to complement each other, handle style variations and highlight properties that identity a character. Two unique strategies were modified to improve the standard GA optimization speed; mutation is used to prevent falling solution into local minima and preventing the chromosomes from becoming too similar to each other. Secondly, modification of fitness function to minimize the recognition errors.

$$\text{Fitness} = (\text{no of selected zero features}) * \%\text{FeatureUsed} \quad (1)$$

where

$$\text{FeatureUsed} = (\text{Hprojection} / (\text{Downsample\_Height} * \text{Downsample\_Width}) * 100)$$

Then followed by feature selection using MGA. The aim is to retain only discriminant features and choose; optimal set from original features for classification task. This minimizes the computational burden imposed by using many features, reduce weighty matrix and character patterns.

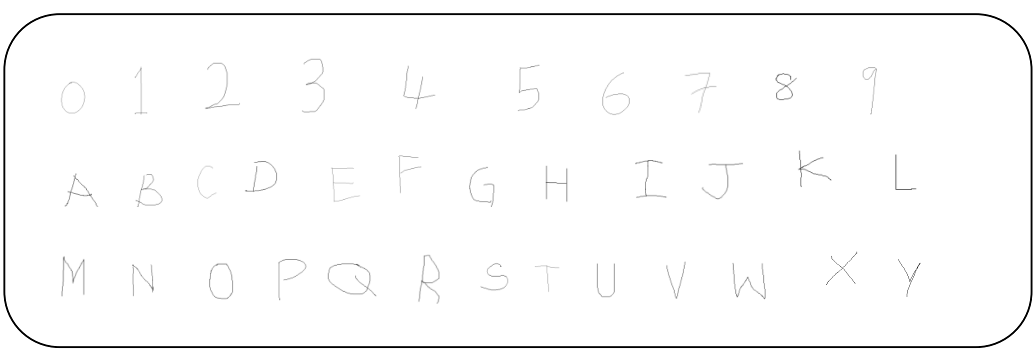

Fig. 1. Shows a sample of dataset used

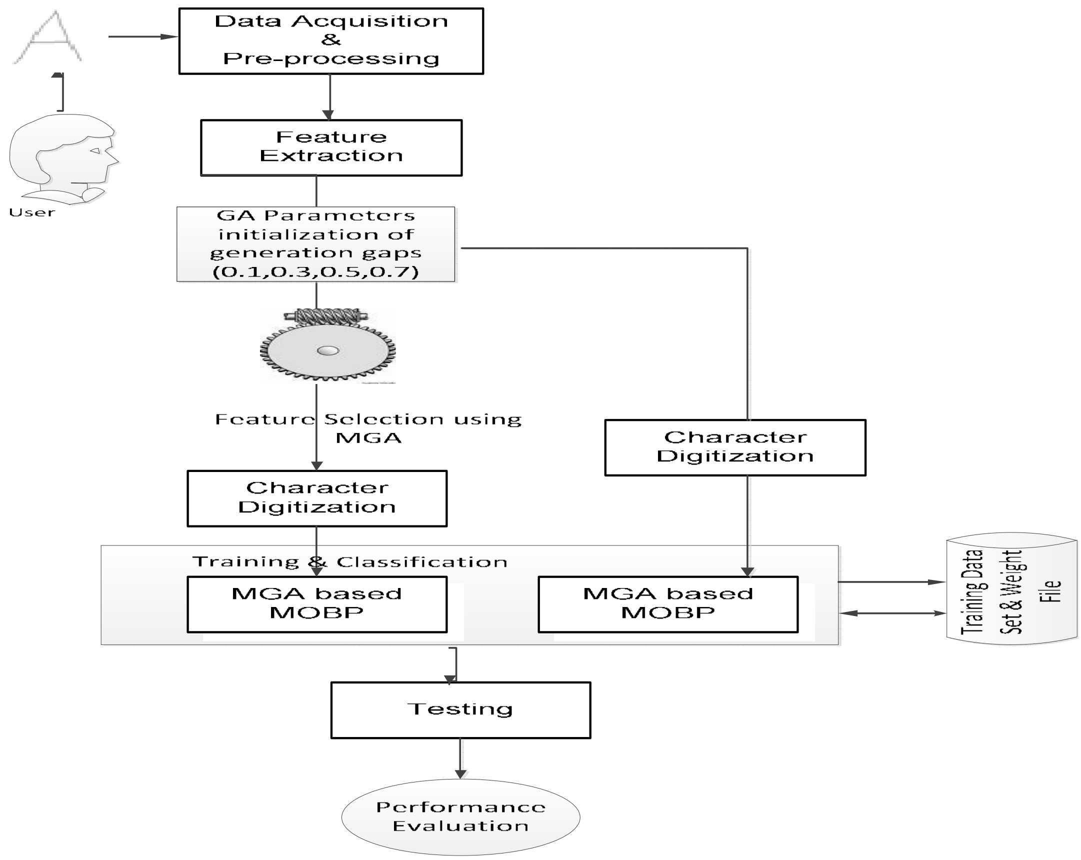

Fig. 2. Block diagram of the developed online handwritten character recognition model

The extracted features were subjected to optimization technique (MGA) for optimal feature selection. The initial inputs of the characters provided are trained with different parameters and different sets of characters. The block diagram shows the training, classification and testing and the training phase contains the handwritten database that was trained. The Model hybridized the modified genetic algorithm and modified optical backpropagation neural networks for the training and classification of the input pattern. The initial inputs of the handwritten characters are trained with different parameters and sets of characters. The characters are classified using two classifiers: C1 and C2. During training, the weights of the network are iteratively adjusted to minimize the error function. The set of outputs obtained are fed into the genetic algorithm to select the best fittest and best solution. The outputs of the genetic algorithm are sent to the neural networks as input. The recognition model involves the usage of artificial neural networks which have been exhaustively trained to recognize different types of handwritten this is achieved by using highly efficient supervised learning algorithm. The output obtained from the trained are stored as files. Match the introduced character with the one in the database template and classify the given character or pattern image. The genetic algorithm is used for optimal feature selection. The extracted features are classified according to similarity of their shapes and features from the dataset collected from different individuals.

3.2.1 The genetic and neural network training algorithm

The training algorithm involves the following two stages:

Stage A: Performs the training of the character sample generated using Genetic Algorithm.

Step 1: Select character samples collected from various people (Generate random population of n chromosomes this corresponds to initial population for the genetic Algorithm).

Step 2: Evaluate the fitness function of the population equation.
Step 3: Mutate new offspring at each locus based on mutation probability.
Step 4: Select parent chromosomes from the population according to their fitness function.
Step 5: Perform crossover on two strongest parents to create a new offspring and replace the weakest parent with the new child created.
Step 6: Replace a fraction of the old generation with new offsprings based on generation gap.
Step 7: Insert the new offspring in the new population and use generated population for further run of the algorithm.

Stage B: Performs the training of the input from the genetic algorithm to the output layer. With the introduction of cubic error function, the modified Optical Backpropagation is given as:

1. Input vector, $\mathrm{X_p} = \mathrm{X_{p1}} + \mathrm{X_{p2}} + \mathrm{X_{p3}} \ldots + \mathrm{X_{pm}}$ to the input units. Each value in input layer receive X_{pi} and forward to values in hidden layer.
2. For each character, calculate the output of the feed forward network.
3. Calculate the cubic error term by comparing with the desired output corresponding to the symbol.

   Using cubic error adjustment where

   Y_{pk} = Desired output, O_{pk}= Network output
   T = $\left(Y_{pk} - O_{pk}\mathrm{l}\right)2$

4. Back propagate error across each link to adjust the weights.
5. Move to the next character and repeat steps 2 to 4 until all characters were visited.
6. Compute the average error of all characters.
7. Repeat steps from steps 2 - 6 until the cubic error was acceptably small or error threshold is reached for each of the training vector pair.

3.2.2 Classification and testing stage

The classification phase is the last stage of the developed character recognition system. This phase determined the overall performance of the developed algorithm. Two types of classifiers were implemented for online character recognition. Two classifiers (C1 and C2) were formulated from MGA-MOBP such that C1 classified using MGA at classification level only while at C2, optimization was used at both feature selection and classification levels.

3.2.2.1 C1 (MGA based MOBP)

Two classifiers (C1 and C2) were formulated from MGA-MOBP such that C1 classified using MGA at classification level. There was no optimization at feature selection, but MGA was employed at classification level and therefore all the features were used.

3.2.2.2 C2 (MGA and MGA based MOBP)

Feature vectors were extracted from raw image data and tested on training dataset to find out the most relevant set to improve recognition accuracy. The features extraction method used consist of stroke information(pressure to be used in writing strokes of the character, number of strokes used in writing the character and projection count of the character), invariant moments (position, size and orientation of the character) and zoning (densities of object pixels in every region, distance of both image centroid and zone centroid are computed) on the character to create a global feature vector. The research combined structural and statistical techniques to solve image style variations, distorted characters and improve recognition accuracy and convergence time.

C2 employed MGA at feature selection level and classified at classification level. The goal for using optimization algorithm at feature selection level is reduce number of features by select features that relevant for classification performance. This reduces computational time, reducing data storage requirements, improve training time, convergence time and recognition accuracy. In this paper, a modified genetic algorithm was used for optimal feature selection. MGA was used during the training to solve the problem of local minima in backpropagation and find the optimal set weights at a very short time. Replace a fraction of the old generation with new offsprings based on generation gap (its effect towards convergence time). The recognition of character is done based on minimum distance classifier between two feature vectors (testing and template of training vectors) which forms the character input pattern using Euclidean distance metric. That is template of when the minimum distance is less or equal to a threshold set implies correct match or a recognized character.

4. EXPERIMENTAL DESIGN AND RESULTS

4.1 Experimental Setup

The development tool used is Microsoft Visual C# version 4.0 on Windows 8 Ultimate 64-bit operating system, Intel®CoreTM i5-3210M CPU @2.50 GHz processor, 8GB Random Access Memory. The decision taken to recognize or classify the images was based on training time, recognition time, correct recognition, false recognition. In this study, training and test sets consist of 6200 and 540 sample images respectively.

4.2 Evaluation Results

Table 1 represented the results of analysis of influence of generation gap on average recognition accuracy and average convergence time. This was achieved by varying the generation gap through 0.1, 0.3, 0.5, and 0.7. The best convergence time and recognition accuracy was obtained as Ggap 0.1 which is 103.20 milliseconds and 99.44% respectively at 6200 datasets. Thus the system recorded its best result at 0.1 generation gap while the accuracy decreased to 98.11% and time value increased 243ms at generation gap of 0.7. This implies that generation gap variation had a positive effect on the network performance. At 0.1 Ggap, the average recognition accuracy is proportion inverse to the convergence time. Replacing a smaller fraction of the population at each generation is more beneficial than replacing a large portion that can lead to lower performance. The intervals of generation gaps have shown reduced convergence time.

Table 1. Effect of variation of generation gap on average recognition accuracy and average convergence time

Generation gap	Average recognition accuracy (%)	Average convergence time (milliseconds)
0.1	99.44	130.30
0.3	98.83	211.69
0.5	98.51	199.23
0.7	98.11	243.00

Table 2 shows results generated with C1 and C2 models highlighting fitness value, average convergence time, False Recognition (FR) and Recognition Failure (RF) at each generation gaps of 0.1, 0.3, 0.5 and 0.7. At 0.7 generation gap, recognition accuracy and fitness values for C1 are 96.7% and 0.245 respectively with False Recognition (FR) value of 3% while the accuracy value increased to 98.7% and FR value decreased to 1.3 % respectively at generation gap of 0.1. However at 0.7 generation gap, C2 recognition accuracy of 98.1% with FR 1.6% while recorded highest accuracy value of 99.4% with FR of 0.6%. Summarily, the recognition accuracy increases with decrease in Ggap of number. This was due to the heuristic nature of the genetic algorithm and larger character samples in the vector space. The smaller the portion of the population that is replaced each generation the better the average convergence time and recognition accuracy. Replacement of large population (that could not tolerate large changes content) can lead to lower performance. At the two classifiers, the fitness function values shown little or no significant level. Thus C2 produced its best result at 0.1 generation gap.

Table 2. Performance evaluation of the classification accuracies of two classifiers

Ggap	C1				C2			
	Fitness value	CR (%)	FR (%)	RF (%)	Fitness value	CR (%)	FR (%)	RF (%)
0.7	0.245	96.7	3.0	0.3	0.245	98.1	1.6	0.3
0.5	0.245	97.4	2.6	0.0	0.245	98.5	1.3	0.2
0.3	0.243	98.3	1.7	0.0	0.244	98.8	1.2	0.0
0.1	0.245	98.7	1.3	0.0	0.246	99.4	0.6	0.0

CR = Correct Recognition, FR = False Recognition and RF = Recognition Failure

5. CONCLUSION AND FUTURE WORK

In conclusion, MGA was used for feature selection to reduce the feature space which enhanced recognition accuracy, reduced training time and resulted to decreasing convergence time; therefore the primary objective of the study is achieved. A model for online character recognition was proposed using MGA and MOPB algorithm for two classifiers: C1 and C2 for overall recognition accuracy. In this investigation altogether MGA has been examined. The influence of genetic algorithm parameter, namely, generation gap, has been employed for aiming to improve the recognition accuracy and convergence time. The results show that there is better accuracy and convergence time as generation gap values decreases. The results obtained show that the convergence time using generation gap of 0.1 instead of 0.7 was the best and reliable with slight improved recognition accuracy. As a result of the findings during the course of study, it is recommended that there could be further research on finger and sentence recognition systems with MGA & MOBP as classifier.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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