A New Approach to Genetic Algorithm in Image Compression

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Abstract

The importance of image compression problem has been progressing with the development of technology. The usage of genetic algorithm has become widespread in this field. In this study, the general structure of genetic algorithm and its effects on image compression are analyzed. In this study, it is seen that the creation of population via natural selection, the ratio of mutation and crossover affect the performance of image compression a lot. Roulette Wheel Selection and Elitist Selection that are the most known natural selections are firstly implemented on the standard image. But with these known natural selections, MSE (mean square error) and PSNR (peak signal noise ratio) are seen close to each other. It is seen that in all implementation with the 10% crossover and 5% mutation ratio, the natural selection algorithm based on pools has better MSE and PSNR values than genetic algorithm based on roulette wheel and elitist selection respectively.

1.Introduction

With the improvement of technology, obtainment of the data swiftly and the necessity of its utilization have increased. This necessity brings along the situation of storage productively, reaching and transmitting of data together [1]. Data compression has a big importance in providing band width narrowing and decreasing in memory capacity. As for image compression, image compression is a technique that is about bit reduction which is necessary for image storage and transmission without noticeable loss of data. There are two types of transmission named lossy and lossless. In lossy technique, there is data loss and original image is reacquired with an acceptable error rate. In lossless compression, there is no loss of data and original image is reacquired with a low compression ratio [2].

Nowadays researchers has been focusing on how to choose and optimize image blocks to balance the speed of compression and decompression for improving image quality before and after compression [3].

Adaptive heuristic algorithms have been used in data compression recently and classified as evolutionary, bio-inspired, swarm intelligence, physical and other bio inspired algorithms [4]. Genetic algorithm is a technique of evolutionary computational research [5].

2.Genetic Algorithm

Genetic algorithm (GA) is a stochastic searching algorithm based on natural selection and has a remarkable characteristic traits like directly implementing on the structural case, no restraint in differentiability, persistence and unimodality of objective function. Furthermore, GA has an implicit parallelism and global optimization accomplishment. As a result of this, GA could find out optimal search space by itself and restore the search direction adaptively not bounded with predictive factors[6]. These characteristic features make GA inclusively applied in many practical optimization problems obtained from various field like machine learning [7], signal processing [8], electronic engineering [9], etc [10].

GA formats the population in the begining of evolution and then performs each steps seen in Fig.1. For each individual, each chromosome consists of 4x4 blocks of standard image. After initialization, GA contains evolutionary operators as natural selection, crossover and mutation and evolves the population to optimize objective function iteratively till ending conditions comes true [10].

2.1. Fitness Evalution and Natural Selection

Natural selection determines whether the individuals belonging present population can survive in the new population falling into crossover and mutation in pursuant of superiority and inferiority of individuals. GA uses fitness value which is figured out by a predefined fitness evaluation function to specify superiority and inferiority of individuals. In this study, the fitness function is determined as Mean Square Error (MSE) of image codebooks whose random combinations are taken as initial population. For the optimal solution of the most representative codebook which might correctly be implemented in the image compression the fitness function is analyzed iteratively.

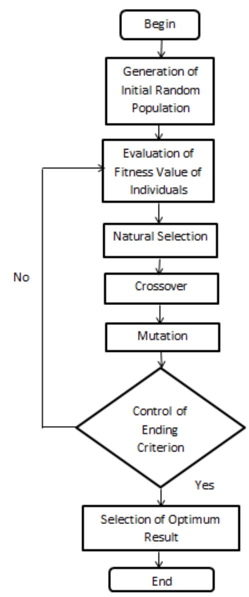

Fig. 1. Flowchart of GA

2.1.1 Roulette Wheel Selection

Roulette Wheel Selection firstly figures out the fitness proportional value of each individual to total fitness value of all individuals representing the probability of the individuals named as p_i shown in Equation 1,

$$p(a_i)= F(a_i) / \sum_{i=1}^{n} F(a_i) \quad (1)$$

where $p=\{a_1, a_2, a_3,\ldots.a_n\}$, $F(a_i)$ is the fitness value of individual, $a_i \in p$ and n is the size of population. The main purpose of this natural selection is to make the individuals that have high fitness value breed more or to make the individuals that have low fitness value breed less or no breed.

The cumulative probability is calculated and the kth individual probability is formulated in Equation 2 as

$$p_x(a_k)= \sum_{j=1}^{k} p_x(a_j), \quad (2)$$

Random number r_s between 0 and 1 is produced and compared with $p_x(a_k)$ to specify selected individual. If $a_{k-1}< r_s < a_k$, kth is selected and it is repeated till n (number of population) individual is generated [11].

2.1.2. Elitist Selection

In selection of codebook, elitist selection is combined with roulette wheel selection. First of all, the individual which has the best fitness value is selected and transferred to the new generation directly and after this, roulette wheel selection is used for the selection of the rest individual [12].

2.1.3. Pool Based Natural Selection

In contrast to the roulette wheel selection and elitist selection, pool based natural selection is comprised of two pools that have individuals with higher fitness values and the rest.

In image compression, each codebook consists of pixels and every pixel has importance for the representation of original image in codebook generation. Because of roulette wheel and elitist selection, the new generation could not have genes that have superiorities or the new generation could have bad chromosome and features. In order to overcome these possibilities, two pools are created and a pool consists of individuals with higher fitness values and the other pool involves the rest. Thus, in every iteration with the other evolutionary operators as crossover and mutation, each individual could have at least a good chromosome and gene. As a result, the degeneration of generations are iteratively precluded.

2.2. Crossover

Crossover operator explores the new chromosomes and gives distinctness in new generation. Crossover is primarily sorted in accordance with application and there are various types of encoding like single point, two point, uniform and arithmetic crossover, etc. In this study, uniform crossover is applied to the population so that pixels are copied randomly from the first or from the second individual [13].

2.3. Mutation

Mutation operator prevents establishing a uniform population which has no ability to evolve and modifies the genes of the chromosomes with a mutation ratio. Like crossover mutation, there are several types of encoding such as pixel inversion, order changing, adding a small number, cut of selected nodes, etc. In this study, after the encoding of crossover, the pixels are selected randomly and added a small number with a delta step iteratively.

While using crossover operator is presupposed to utilize prevalent solution for finding better ones, mutation operator is presupposed to assist for the examination of total search space and to sustain genetic diversity of each individual [13].

3.Vector Quantization and Linda Buzo Gray Algorithm

R. M. Gray, N. M. Nasarabadi and R. A. King made a present of vector quantization (VQ) that has been a lossy compression technique and used in the literature for a long time [14,15]. Among the lossy compression techniques, this method is the most popular and widely used technique. The vector quantization depends on the quality of the codebook being used [16]. It affects the efficiency and the quality of the quantizer. But since it is based on block coding and a fixed length algorithm, it is a hard problem for the multidimensional union. Because of this necessity, Linde Buzo Gray (LBG) suggested a training sequence and this has overcome the multidimensional necessity [17]. In this algorithm, determination of an initial codebook which consists of codewords that is a set of training sample concerned with VQ encoding forms a basis for the population [18].

4. Experiments and Results

After the implementation of GA with the roulette wheel selection, the elitist and pool based natural selection to the population comprising 8 codeword number, it can be seen in Table 1 that there is a critical difference in MSE and PSNR. In comprasion, GA with Pool Based Natural Selection has better performance in MSE and PSNR than Roulette Wheel Selection and Elitist Selection respectively. In Figure 2 the MSE change of the best individuals in population with 8 codeword and 100 iteration number could be observed and it shows that Pool based GA has the lowest MSE .

Table 1. The results of GA with various natural selection applied to the population that has 8 codeword numbers

Lena	Roulette Wheel Selection	Elitist Selection	Pool Based Natural Selection
Codeword Number (vector)	128	128	128
Compression Ratio (bit per pixel (bpp))	0.0254	0.0254	0.0254
MSE	327.8592	338.7513	320.5201
PSNR (db)	22.9739	22.8319	23.0723

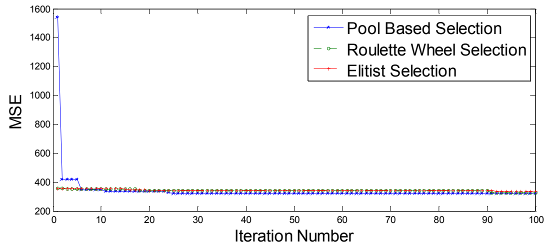

Fig. 2. MSE change of the best individuals in population with 8 codeword number

When these algorithms are applied to the population comprising 16 codeword number, GA with Pool Based Natural Selection has better performance in MSE and PSNR than Roulette Wheel Selection and Elitist Selection (Table 2). In Figure 3 MSE change of the best individuals in population with 16 codeword and 100 iteration number could be seen and it is obvious that GA with Pool Based Natural Selection has the lowest error rate .

Table 2. The results of GA with various natural selection applied to the population that has 16 codeword numbers

Lena	Roulette Wheel Selection	Elitist Selection	Pool Based Natural Selection
Codeword Number (vector)	256	256	256
Compression Ratio (bpp)	0.0352	0.0352	0.0352
MSE	258.7379	260.1108	245.8341
PSNR (db)	24.0022	23.9792	24.2249

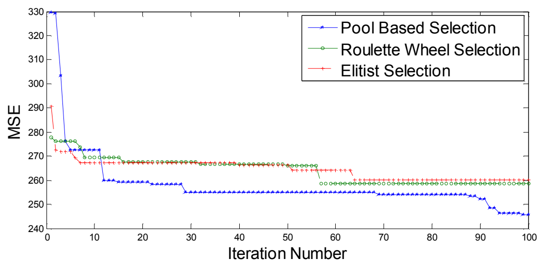

Fig. 3. MSE change of the best individuals in population with 16 codeword number

Upon applied to the population with 32 codeword numbers, GA with Pool Based Natural Selection has better results in MSE and PSNR than Roulette Wheel Selection and Elitist Selection iteratively (Table 3). As in other figures, Figure 4 shows the MSE change of the best individual in population with 32 codeword and 100 iteration number and the lowest MSE is belonging to Pool Based GA.

Table 3. The results of GA with various natural selection applied to the population that has 32 codeword numbers

Lena	Roulette Wheel Selection	Elitist Selection	Pool Based Natural Selection
Codeword Number (vector)	512	512	512
Compression Ratio (bpp)	0.0468	0.0468	0.0468
MSE	204.1146	205.2041	185.9518
PSNR (db)	25.03206	25.0089	25.4368

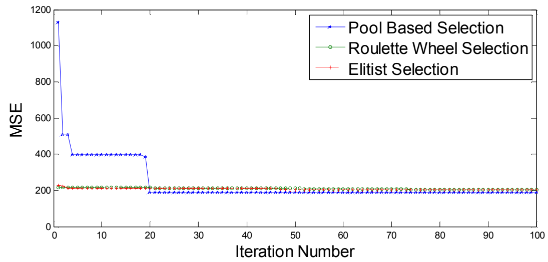

Fig. 4. MSE change of the best individuals in population with 32 codeword number

Finally, after the implementation on population with 64 codewords, like the others Pool Based GA has better results than Roulette Wheel Selection and Elitist Selection respectivelty (Table 4). Figure 5 shows MSE change of the best individuals in population with 64 codeword and 100 iteration number. As in other GA , Pool Based GA has the lowest MSE and better performance in comparison to other natural selection based GA. Figure 6 shows the reconstruction of Lena after the implementation of GA with Roulette Wheel, Elitist, Pool Based Natural Selection respectively on population that has 8, 16, 32, 64 codeword number step by step from the first row to the last row. There are not explicit differences between them if someone does not look carefully.

Table 4. The results of GA with various natural selection applied to the population that has 64 codeword numbers

Lena	GAwith Roulette Wheel Selection	GA with Elitist Selection	GA with Pool Based Natural Selection
Codeword Number (vector)	1024	1024	1024
Compression Ratio (bpp)	0.0625	0.0625	0.0625
MSE	165.0547	165.0665	164.5081
PSNR(db)	25.9545	25.9542	25.9689

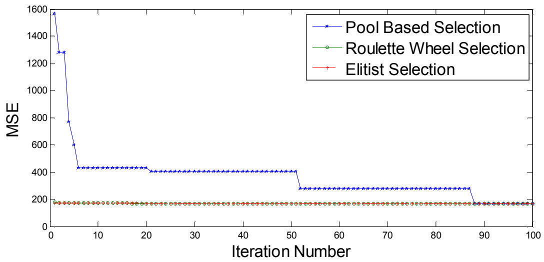

Fig. 5. MSE change of the best indiviuals in population with 64 codeword number

Fig. 6. Reconstruction of Lena after the implementation of GA with various natural selection in population that has 8, 16, 32, 64 codeword number from above to below row (Roulette Wheel, Elitist, Pool Based Natural Selection respectively)

5.Conclusion

From the results, it can be seen that GA with Pool Based Natural Selection has the best performance in each codeword numbers after 100 iteration in comparison to Roulette Wheel Selection and Elitist Selection. In this paper, GA is applied by different natural selection to find the most representative codebook that has better fitness value in image compression. To expedite evolution and prevent the solution from getting out of searching space, tuning crossover and mutation ratio are firstly determined specifically. With this study, it is obviously observed that there would be a further study of GA to increase the quality of reconstructed image as well as fine tuning of operators.

6.References

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