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SIGNIFICANCE OF PARAMETERS IN GENETIC ALGORITHM, THE STRENGTHS, ITS LIMITATIONS AND CHALLENGES IN IMAGE RECOVERY

Samer M. Shorman and Sakinah Ali Pitchay
Faculty of Science and Technology, Universiti Sains Islam Malaysia (USIM), Bandar Baru Nilai, Nilai, Negeri Sembilan, Malaysia
E-Mail: shormansamer@yahoo.com

ABSTRACT

The Genetic Algorithm (GA) is becoming very attractive and suitable for solving problems where high computational performance is required. This paper describes theoretical aspects of genetic algorithms which are parameters used to get a result such as crossover, mutation, selection and fitness. Likewise, GA performs efficient search spaces to get an optimal solution. This paper also highlights several issues in which GA as a tool for recovering the image in variety domain. Generally, however this approach has some limitations, strengths and challenges that are also discussed in this paper. Findings on a simple simulation of GA are also presented.

Keywords: genetic algorithm, evolutionary algorithms, strengths, limitations, image recovery.

INTRODUCTION

Genetic algorithms (GAs) have been used in numerous fields to solve problems, especially when dealing with problems with very large search spaces. A lot of methods have been proposed to recovery images such as Wiener filter, Lucy Richardson and evolutionary technique. Many of other algorithms used according on the kind of images. For example medical images have different techniques, while 3D image has other algorithms. On the other hand evolutionary technique was used to solve image recovery problem, such as Genetic algorithm that will discuss in this paper. It is a stochastic search to find optimal solution that utilizes the principles of natural selection, and inspired by the biological organisms, to solve a problem within a complex search space (Aravind *et al*., 2011).

Genetic algorithm has been developed by John Holland (Srinivas and Patnaik, 2012) at the University of Michigan in 1970. Their research goals were to abstract and explain the adaptive process of natural systems and to design artificial system software that retains the important mechanisms of natural selective processes (Tippabhatla, 1998). Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics, genetic algorithm uses a fitness function to determine the performance of each artificial chromosome. Since the fitness function is intended to measure the restoration quality (Chow *et al*., 2001).

In (Khurana *et a*l., 2011) One significant application of GA is to search complicated spaces and function optimization. It has initiatedits search with the random solution of the problem. The basic concept of genetic algorithms is designed to simulate processes in natural system necessary for evolution. This represents an intelligent exploitation of a random search (Bajpai and Kumar, 2010). Some of their implementations are very different from the traditional simple GA, especially with population structure and selection mechanisms. It uses probabilistic transition to guide itself toward an optimum solution, where its cost function is to be minimized (Chen et al., 1996). In (Papadopoulos and Wiggins, 1998) present a system for the generation of jazz melodies, this system often generates interesting music styles.

Many GA have been developed such as SGA and PGA since the traditional GA was proposed by Holland in 1975 (Holland, 1992) the difference between the parallel Genetic algorithm (PGA) and the simple Genetic algorithm (SGA) is that the PGA divides a population into several smaller subpopulations and executes the main loop of the SGA on each subpopulation separately.

PGA selects the best individual with the highest fitness from each sub population and migrates it to different subpopulation, where the worst individual with the lowest fitness is replaced by the winning individual from the adjacent subpopulation. Furthermore, the PGA based on Island model to implement the threads. For measurement of the performance, which is the dependence of SGA on the population size with one single processor? Moreover, the simulation results show that the parallel algorithm achieves a speedup with the number of processors, while keeping the performance as well as or better than the traditional SGA (Chen *et al*., 1996).

The accuracy of solutions obtained by genetic and evolutionary computation is better than that obtained by other methods such as conventional methods, NNs and SA. However, it requires more computation time. This result allows us to realize efficient and robust systems for optimizing image processing (Shimodaira, 2000).

Genetic algorithm was applied widely in image processing, which is considered an optimization problem. For example, such as in image restoration, segmentation, enhancement, and image retrieval via interactive genetic algorithm (Dass *et al*., 2014). On the other hand, various algorithms were used to restore image such as statistical methods and evolutionary algorithm methods, which are known for their flexibility and ability to work in large search spaces. For that these methods are used in image processing, because of their ability to solve problems high

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complexity relatively fast such as genetic algorithm to restore images (Burgos-Artizzu *et al*., 2008). Moreover, using the parallel genetic algorithm (PGA) with Hopfield neural network (HNN), by combination between the advantage of PGA parameter selection and then uses Hopfield NN to train sample efficiently, to get the advantage of both PGA and HNN, The recovery image has a better effect in vision and quantitative.Likewise, the genetic algorithm is effective for image restoration (Sun and Wu, 2010). In the research of (Bo-chang, 2010), they present Simulated Annealing Genetic Algorithm for image recovery, where they found that the algorithm has a higher sufficiency, and the restored image still has a certain degree of noise.

In (Suthaharan *et al*., 1997) proposed a technique using the Genetic Algorithm to find the optimal value of the ratio R , which is a priori knowledge of the signal-to-noise ratio, in the Wiener Algorithm to image restoration, the simulation shows using GA can be extended to the optimization of are in the Wiener Algorithm with respect to blur degradation. In (Farooq *et al*., 2012), that implemented updated on genetic algorithm; by adding new parameter Pooling Operator which is It is a new operator we are introducing in GA. The term pooling refers to creating a pool of chromosomes to be used in the algorithm. To increase the convergence rate, that used adaptive crossover rate and mutation rate. The new algorithm starts with pooling which is get the generation with their fitness. Pooling affects the results number of iterations reduces, MSE value is more accurate and convergence is higher.

In (Toledo *et al*., 2013), proposed a novel image denoising method based on a genetic algorithm. The population is initialized every time a convergence occurs, when only the best individual (image) is kept for the next stage. The results show that the proposed method is competitive in comparison with state-of-the-art approaches. In (El-Regaily *et al*., 2012) they proposed technique using Lucy-Richardson algorithm is used to find candidate restored images within the algorithm. The GA starts on a random basis then converges to the best entity that restores the blurred image with the minimum error that corresponds to the highest probability. Furthermore in other research by integrating feature of compressive sensing and genetic algorithm which can look foroptimal solutions to get the best recovery image. The results show that the method not only has better recovery quality and higher PSNR, but also can effectively avoid the premature convergence problem and achieve optimization steadily (Lin, 2012).

Generally, all of this state-of-art which mentioned before about using GA or combine GA with other algorithms on image recovery demonstrates a lot of advantages, disadvantage and limitations for using GA in image recovery, many of these features inspired from evolutionary algorithm characteristics.

Evolutionary algorithm

Evolutionary algorithms (EAs) are inspired by the biological model of evolution and natural selection first proposed by Charles Darwin in 1859. In the natural world, survival of the fittest, evolution helps species adapt to their environments (Daniel, 2008) Organisms that most fit to their medium will tend to survive the struggle for existence environmental factors that influence on survival prospects for an organism includes climate, availability of food and the dangers of predators.

EA is simple and strong, it has a lot of properties such as adaptability, self-organizing, self-learning and balanced in its composition. EA is a technique presented in processes as in Figure-1. EA has properties which are an indirect effect on the solution space, and use the updating population in the next generation as a native solution space. It aims to find solution in multiple points via random transfer rules, for these properties which mentioned before.

EA finds an optimal solution high probability, using information about the fitness function. This algorithm is clearly rising in the optimal solution, artificial intelligence, machine learning, problem solving, image processing and computer vision (Li and Yang, 2010).

Evolutionary algorithms were introduced for a perfect solution for many problems. Thus, this research will use genetic algorithm which is a part of evolutionary algorithms. It acts on use elements current generation to create an entirely new generation of the same size, to exploring an optimal solution in the search space (Snyers et al., 1995).

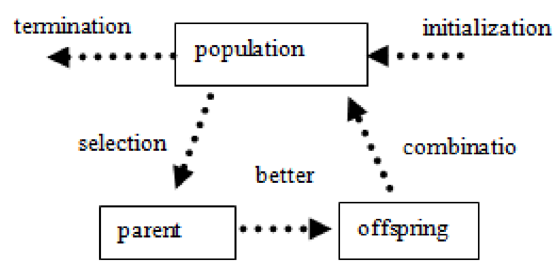

Figure-1. Evolutionary algorithm processes.

The conventional methods in image enhancement use optimization approach where the objective function (fitness) relies on a good initial value of the hyper-parameters in order to get a better recovered image (Kaban and Pitchay, 2013), (Pickup, 2008), (He and Kondi, 2003), Hardie *et al*, 1997). A lot of researches discussed the advantage and disadvantage for EA. Moreover, GA is the algorithmof EA. The next section will explain the phases, strengths and limitations of GA as the following.

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GENETIC ALGORITHM

Genetic algorithm phases

Genetic algorithm is a good search algorithm based on technique of natural selection and natural genetics. It uses rules to guide itself toward an optimal solution, where its cost fitness function is to be minimized compared with other search algorithms (Holland, 1992). The process in GA as the following:

1) Initial population in SGA is a candidate solutions are usually generated randomly across the search space. But in PGA divided the main population into N sub population.

2) Reproduction generational that is population is probably replaced at each generation

3) The fitness function is the objective function to be optimized, provides the mechanism for evaluating each string.4) Selection that is select a solution with higher fitness values,. Therefore, many selection procedures have been proposed such as roulette-wheel.

a) Roulette Wheel selection with take in consideration fitness-based selection (Khurana *et al.*, 2011). Therefore, each chromosome such as [1111001001, 0010110010] has a chance of selection that is directly to fitness.

b) Rank-based selection, selection probabilities are based on a chromosome's relative rank or position in the population, more than fitness.

c) Tournament-based selection the original tournament selection is to choose K parents at random and returns the fittest one of these.

5) Mutations occur randomly, some mutations will be advantageous. Mutation of a bit involves flipping it as changing a 0 to 1 or vice versa (Srinivas and Patnaik, 1994), (Paulinas and Ušinskas, 2007). The mutation process shows as the following:

M= 01000010 M1=01000100

6) Crossover is a GA crucial operation because in this recombination part of two or more parental solutions is to create new chromosomes possibly a better solution, pairs of strings are picked at random from the population and the crossover methods such as

1- Single-Point
Chromosome 1 :**0 1 0 0 0** 0 1 .... **0 1 0 0 0** 0 0
Chromosome 2 :1 1 1 0 0 0 .... 1 11 0 0 1
2- Two-Point
Chromosome 1 :0 1 **0 0 0** 1 .... 0 1 **0 0 0 0**
Chromosome 2 :1 1 1 0 0 0 .... 0 1 1 0 0 1

7) Termination the conditions for terminations are represented, in the total number of fitness evaluations reaches a given limit, and fitness remains under a threshold value, for a given period of time.

Flowchart of GA

Figure-3 shows GA flowchart to expound the processes through GA which based on fitness function evacuation (Bo-chang, 2010).

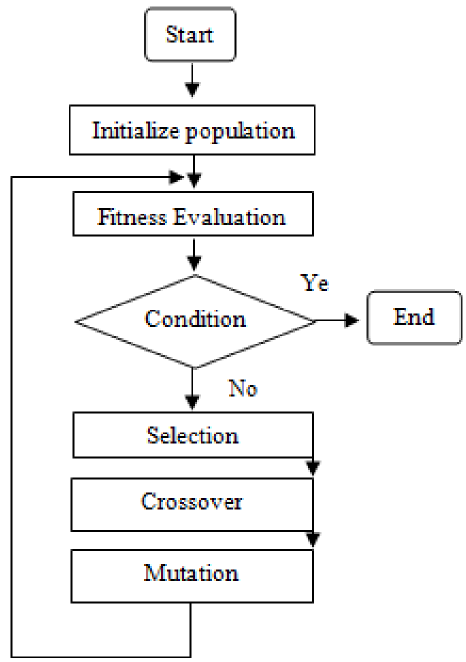

Figure-2. Genetic algorithm flowchart.

GA processes to produce new population of chromosomes by selecting the better fit solutions from the population and implement GA procedures to produce new generation of the solutions. This operation is repeated until criteria is met acceptable result is found (Khurana et al., 2011).

Binary encoding

Binary coding is the most common in GA mainly because the GA used this encoding. In the binary encoding every chromosome is a string of bits, 0 or 1. Binary coding gives many possible chromosomes even with a small number of bits. Therefore, this encoding is often not natural for many problems thus must be made after crossover and mutations to other form such as chromosome could be bit strings as in Figure-4.

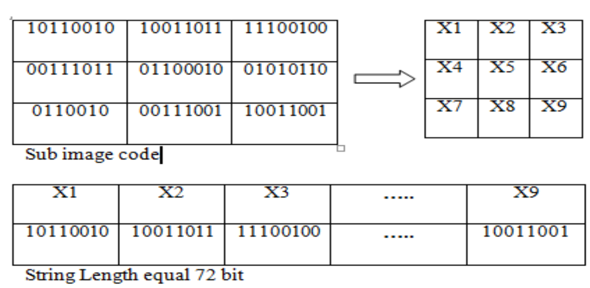

Figure-3. Binary code presentation.

STRENGTHS OF GA

1) A genetic algorithm has ability to many parameters simultaneously (Forrest, 1993). Many problems cannot be stated in terms of a parameter, but must be expressed in terms of multiple objectives, GAs are very good at solving problems: in particular, that use of parallelism enables them to produce multiple equally good solutions to a problem, possibly one candidate solution optimizing one parameter and another candidate optimizing a different one.

2) GA with feature of parallelism that allows them to implicitly evaluate many schemas at once, GA well-suited to solving problems where the space of all potential solutions is truly huge too vast to search exhaustively in any reasonable amount of time. The problems that into this classification are known as non-linear which mean non linearity is changing one component may have effects on the full system, and many changes that individually are detrimental may lead to much greater improvements in fitness when combined. While a linear problem, the fitness of component is separated, any improvement to any one part will result in an improvement of the system as a whole, few real problems are like this category.

3) GA perform well in problems for which the fitness landscape is complex - ones where the fitness function is discontinuous, changes over time, or has many local optima. Most problems include a wide area for solution (Craenen *et al*., 2001).

4) Crossover is the most important step in the context of genetic algorithm. Crossover is the key element that distinguishes genetic algorithms from other methods. Without crossover, each individual solution is on its own, exploring the search area in its immediate neighborhood without reference to what other individuals may have discovered. In crossover there is a transfer of information between successful individuals, who can benefit from what others have learned, and schemata can be combined, with the potential to produce an offspring that has the strengths of both its parents (Koza, 1999).

5) Most important point is that GAs is parallel. Majority other algorithms are serial and can only explore the solution area to a problem in one trend at time, and if the solution they discover turns out to be suboptimal, there is to do but leave all work previously completed and start over. However, since GAs can explore the solution space in multiple trends at once. If one path turns out to be a dead end, they can easily remove it and continue work on more favorable methods, giving them a greater chance each run of finding the optimal solution (Burke *et al*., 1995).

6) Genetic algorithms know nothing about the problems they are solved. Likewise, using previously known domain-specific information to guide each step and making changes with a specific improvement, they make random changes to their candidate solutions and use the fitness function to define whether those changes produce an improvement

LIMITATIONS OF GA

1) Fitness function should be considered a higher value is attainable, and equate to a better solution for the given problem. If the fitness is chosen poorly or defined inaccurate, the GA may be unable to find a solution to the problem, or may find wrong solving for this problem.

2) Most important, consideration in originate a genetic algorithm is defining a representation for the problem. The language used to define candidate solutions must be robust; it must be able to tolerate random changes such that errors do not consistently result.

3) Choice of fitness function, the other parameters of a GA the size of the population, the rate of mutation and crossover, which making a good prediction for the type and strength of selection must be also chosen with carefully. If the population size is simple, the genetic algorithm may not enough to discover of the solution space to consistently find good solutions.

4) Genetic algorithm is one type of problem that have difficulty dealing with the problems that deceptive fitness functions (Mitchell, 1998), those where the locations of improved points give misleading information about where the global optimum is likely to be found.

Genetic algorithms against analytically solvable problems. Based on several researchers are against using GA on problems has analytically solvable. It is not that genetic algorithms cannot find good solutions to such problems; it is merely that traditional analytic methods take much less time and computational effort than GAs are usually mathematically guaranteed to deliver the one exact solution (Forrest, 1993), (Holland, 1992).

5) Precocious convergence which is one known problem that can occur with a GA. If an individual that is more appropriate than most of its competitors emerges early on in the course of the run, those individuals which better, may go down between the populations, which mean rise local optimum for individuals rather than searching the fitness enough to find the global optimum (Forrest, 1993), (Mitchell, 1998).

RECOVERING IMAGES USING GENETIC ALGORITHM

Image recovery

Image recovery refers to restoration more accurate, in order to removing the degradation like blurring and noise. Image recovery, in many applications such as protecting the cultural and arts, remove objects, virtual life, restoring old images (Li and Yang. 2013). Color image recovery can be performed to restore colors from gray images (Lin *et al*., 2014). On the other hand, many reasons related in image blur come from the motion between camera and object.

Therefore, the definition of degradations in the imaging systems means that images affected by blurring and noise to the output images. Likewise, blurring almost arises from the optical motions in the camera, and noise is caused by error pixels in camera sensors, or transmission between devices (Zhang *et al*., 2012). All of these

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influences on the images causes mess analysis which is led weak in recognizing objects in the images (Gonzalez and Woods, 1992). The technique of image recovery which used to rebuild the images that have degradations, to enhance the image vision and understanding.

Challenges of image recovery using GA

Many of the restrictions still faces image recovery by GA, a lot of these conditions inspired from the GA limitations such as the methods will represent the problem in genetic algorithm and which language is best used to define candidate solutions, poorly chosen for Fitness or inaccurate. Likewise, the most important side about to configuration of GA parameters. Such as the size of the population, the rate of mutation and crossover, which are influenced to make a good recovery (Mitchell, 1998). Moreover, traditional analytic methods take much less time and computational effort than GAs is usually mathematically guaranteed to deliver the one exact solution (Holland, 1992). and Precocious convergence which is one known problem of a GA means some ofthe best solutions, that are not chosen for the next generation. (Forrest, 1993).

The discussion of image recovery which is a complex problem and a good to use the optimization theory in GA, to find optimal recovery. Therefore, to investigate about the features in image recovery, such as observation of noise, estimation the prior knowledge, huge searches space, and discrete, continuous search space. Those properties make image recovery as a type of hard problems can be solved in optimization methods using GA (Wang and Fan, 1996). The challenges to adapt the genetic algorithm to restore the images with considering an accurate and time consuming, first encode candidate solutions to the problem. The simplest encoding as chromosome, and that used by many GAs, second requirement for applying evolutionary algorithms is that there must be a way of evaluating partial solutions to the problem, such as fitness function (Daniel, 2008). In the GA method, it does not require to initialize the specific value of the hyper-parameters. In other words, GA method allows many initialization values for the hyper-parameters and the best one will be chosen according to the selection process in the GA. Furthermore, GA's are extensible, easy to hybridize and easy to interface genetic algorithms to existing simulations and models (Goldberg, D. E, 1989).

According to (Pitchay, 2013), evolutionary algorithms are heuristic global optimisers that have the ability to find good quality solution (approximate solution) to difficult optimisation problem. However, the performance in EA is degrades in high dimensional problems. Indeed, scaling up evolutionary algorithms to high dimensions is recognise to be a major challenge. The author states that contests are organised at the CEC conference. The larger the dimensionality in the latest competition was 1000. This would correspond to recovering an image no larger than 31 × 32. Yet in (Pitchay, 2013) thesis, the author had tackled a problem for 100 × 100 images where the number of pixels is 10 times bigger than the largest problem so far attempted by the best evolutionary algorithm in the competition. So far, they have tackled for gray scale natural images. The challenges here are to employ GA in a high dimensional problem where many of the existing works do not mention their image size.

Surveillance parameters

GA acquisition much popularity in solving nonlinear problems with its ability to handle all such spaces, including multimodal, constrained and discontinuous space.

The parameters in GA that used different parameter values of parameter settings, which are five parameters in GA in the experiments: population size, number of generations, selection, crossover rate, and mutation rate. All parameters influenced directly on the solution in GA. Therefore, the selection value represents a serious challenge for GA (Hermadi et al., 2010).

Estimated PSF using GA

Image restoration non-blind deconvolution which based on Point Spread Function (PSF). The (Shimomukai et al., 2011) presented a proposed method to estimate PSF by GA. A blurred or degraded image can be approximately described in equation 1:

$$g = PSF * f + N \tag{1}$$

g = blurred image
h = distortion operator called PSF
f = original true image
N = denoted to additive noise

The proposed method to the estimation method of the PSF by using GA, which is adopting the slipstream images as a fitness function. The result present the restored images indicate the effectiveness, and the method can estimate the PSF of real shaking blurred image more accurately.

3D images recovery using GA

3D images is displayed of objects on the computer in three dimensions, it describes an image that provides the perception of depth, so that users feel as in the virtual reality. Genetic algorithm is performed for focus measure optimization. GA finds the maximum measurement by a fitness function, to get better analysis of 3d images. Then 3D shape of the object is determined by maximizing focus measure along the optical direction (Lee *et al*., 2013).

In conventional GA has a very poor local performance because of the random search of GA. Several features are added and some extensions are also made to improve the performance of the conventional GA such as elitist strategy and the result shows effective than the Wiener technique (Jiang, 2000).

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Medical images recovery by GA

Medical imaging is the technique and art of representation the body, to allow doctors to get very precise clinical analysis. Medical imaging aims to reveal internal structures to view of certain parts of the body, to make it possible to identify human problems. (Cho *et al*., 1993). Generally medical images have poor contrast along with serious types of noises, medical images often corrupted by noises due to some factors such as machine specifications, detector specifications and surroundings.

In (Mukhopadhyay and Mandal, 2013) proposed a novel technique which is aimed to recover the original image, it used GA to search the corrected threshold value and the value of the decomposition level. GA searches for a value which is a small correction to the BayesShrink and the corresponding decomposition level. Likewise, GA used very effectively to search the pair of wavelet parameters such as the optimal threshold and the value of decomposition level.

Colore and binary image recovery employ GA

A color image that contains the red, green, and blue colors, but binary images which are black and white that called bi-level images. Binary image is used in various implementations such as line art, and vehicle license plates. industrial and sensor systems that used binary images in the operations. for that GA used in image processing, because of their ability to solve problems high complexity relatively fast such as genetic algorithm to restore binary image (Burgos-Artizzu *et al*., 2008).

Advantages of image recovery using GA

Using EA or GA introduce a good feature to find a solution for the particular problem. main strong points in image recovery by GA such as the following. GA has ability to many parameters simultaneously (Forrest, 1993). Many problems cannot be stated in terms of a parameter, GA can work parallelism that allows them to implicitly evaluate many schemas at once, GA will presents solving problems for all potential solutions. On the other hand, important attributes in GA introduce solutions while it is known nothing about the problems they are solved. these features are appropriate to solve image recovery problem. GA has ability to work with a complicated problem such as image recovery. Furthermore, to utilize get good solution in image restoration of GA, by selection next generation to avoid one of a GA weak point will apply technology as the following.

Elitism

When applying genetic algorithms classical binary form maybe contain some of chromosomes, that are unable to continue for good due to a lot of random processes such as mutation or crossover. The aim of this mechanism to ensure the continuity of good chromosomes using the method of elitism, which is a good move chromosomes directly to the next generation without that apply to any of the operations of genetic algorithms. The pros of this method is the increase in the effectiveness and speed of the algorithms in the access to resolve elitism would bring down convergence time(Lukac et al., 2004).

Mating

The process of mating between chromosomes to produce a new generation, of similarities to what is in the meiosis genes of living organisms upscale. Crossing over summed up this process in the so-called cross or chromosomal exchanges that are also determined randomly, kinetochore which is a point to determine detailed exchange (Vose and Michael, 1999).

Methods of fitness generation

Fitness function generation means find a relation between the data, of expectation new value in the future. There are two methods under title prediction equation:

1) Regression equation analysis which is used in the data set to find any relationship between data (Armstrong and Scot, 2012).

2) Response surface methodology (RSM) explores the relationships between several explanatory variables and one or more response variables. (Jaya *et al*., 2013).

These statistical methods to generate the fitness function when you have real data, By this relation between sub data, we can estimate new values for the other dataset in the future.

FINDINGS

Simple simulation for minimum value

To explain the mechanism of GA will perform this simple simulation as the following: As we have seen below in Figure-5, there are nine of natural gas wellheads and one delivery point (1, 2, 3, 4, 5, 6, 7, 8, 9). Wellhead 1 is closest to the delivery point only; the process will be pumping the output of eight wellheads to the delivery point through. The paths between wellheads have different cost (length). The problem is to find a minimum path cost (length) that connecting all well heads with delivery point without interruption.

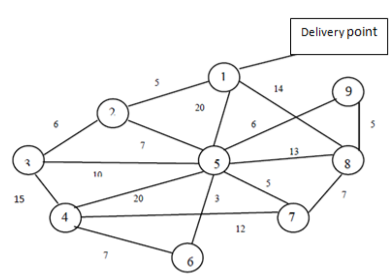

Figure-4. Pipeline network of wellheads natural gas.

An initial population of solutions is selected, fitness is computed for each of the individuals in the population, reflecting the way each individual is, in comparison to the others

Table-1. Initial population and path fitness.

Chrom	Chrom _nodes	Fitness
C1	9 8 7 5 6 4 3 2 1	53
C2	2 3 4 6 7 8 9 5 1	1066
C3	6 5 9 8 7 4 3 2 1	59
C4	4 5 7 8 9 6 3 2 1	2048
C5	9 8 7 4 6 5 3 2 1	55
C6	3 2 5 6 4 7 8 9 1	1047

In Table-1, six chromosomes are generated randomly to form an initial population with the cost of six paths that was selected randomly to represent initial population,

Table-2. The cose between all wellheads.

Nodes	1	2	3	4	….	9
1	-----	5	1000	20	….	1000
2	5	-----	6	1000	…..	1000
3	1000	6	-----	15	…..	1000
….	….	….	….	….	….	….
9	1000	1000	1000	1000	….	-----

In Table-2, the cells with 1000, they represent that there is no direct link between those nodes. Because, 1000 is too big compared to other small costs, therefore ignore those big numbers. Then to create a new population as the following:

Parent 1: **C1**: 9 8 7|5 6 4 3 2 1 Offspring 1: **C7**: 9 8 7 6 5 4 3 2 1
Parent 2: **C3**: 6 5 9|8 7 4 3 2 1 Offspring 2: **C8**: 6 5 9 7 8 4 3 2 1
and mutation for C5 as follow: **C5**: 9 8 7 **4 6** 5 3 2 1 Offspring 3: **C9**: 9 8 7 **6 4** 5 3 2 1

Table-3. New generation and a fitness cost.

Chrom	Chrom _nodes	Fitness
C7	9 8 7 6 5 4 3 2 1	1061
C8	6 5 9 7 8 4 3 2 1	2042
C9	9 8 7 6 4 5 3 2 1	1060
C1	9 8 7 5 6 4 3 2 1	53
C3	6 5 9 8 7 4 3 2 1	59
C5	9 8 7 4 6 5 3 2 1	55

In Table-3, as we seen above, the result shows that the best path is C1: 9 8 7 5 6 4 3 2 1, fitness = 53 because this path has the minimum cost with no interruption, the results show that GA gets close to optimum very quickly. In GA the termination of implement Iterative the phases of the population when the criterions has achieved.

CONCLUSIONS

GA is constantly gaining popularity in many fields. Various tasks from basic level to an optimal solution, the algorithm allows to perform a robust search without trapping in local extremes. This paper concludes describes the three types of crossover and also discuss the strengths and limitations of GAs. On the other hand, the previous theoretical study on image recovery using GA demonstrates that the GA can introduce better solutions in some cases, by recovering image with good quality. Likewise, the results of experiment in this paper show that GA gets close to optimum very quickly, and the probability of change a population is more efficiency through perform the GA phases. In future work, can apply the GA on the problems that have a large complexity such as feature extraction and pattern recognition.

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REFERENCES

Ali Pitchay S. 2013. Advances in Single Frame Image Recovery. PhD Thesis, University of Birmingham, UK.

Aravind I., Chandra M., Guruprasad P. Sarathi R and Samuel D. 2002. Implementation of Image Segmentation and Reconstruction Using Genetic Algorithms. IEEE ICIT'02, Bangkok, Thailand.

Armstrong and Scot J. 2012. Illusions in Regression Analysis. International Journal of Forecasting doi:10.1016/j.ijforecast.

Bajpai P and Kumar M. 2010. Genetic Algorithm- an approach to solve global optimization problems. Indian Journal of computer science and engineering. 1(3): 199-206.

Bo-chang L., Guang-hong H and Xiao-yong W. 2010. Improved Simulated Annealing Genetic Algorithm Applying in Image Restoration. In: Photonics and Optoelectronic (SOPO), 2010 Symposium on (pp. 1-3). IEEE.

Burgos-Artizzu X., Ribeiro A., Tellaeche A and Pajares G. 2008. Optimisation of natural images processing using different evolutionary algorithms. In Evolutionary Computation, 2008. CEC 2008. IEEE.

Burke K., Elliman D and Weave R. 1995. A Hybrid Genetic Algorithm for Highly Constrained Timetabling Problems. International Conference on the Practice and

Theory of Automated Timetabling, Napier University, Edinburgh, UK.

Chen Y., Nakao Z and Fang X. 1996. A parallel genetic algorithm based on the island model for image restoration. In Neural Networks for Signal Processing VI. Proceedings of the IEEE Signal Processing Society Workshop. (pp. 109-118). IEEE.

Cho Z., Jones J and Singh M. 1993. Foundations of medical imaging. pp. 71-84. New York: Wiley.

Chow C., Tsui H., Lee L and Lau T. 2001. Medical image registration and model construction using genetic algorithms. In Medical Imaging and Augmented Reality. Proceedings. International Workshop on. pp. 174-179. IEEE.

Craenen B., Eiben A and Marchiori E. 2001. How to Handle Constraint with Evolutionary Algorithm. In L.

Chambers (Ed.), The Practical Handbook of Genetic Algorithms: Applications, 2nd Edition, volume 1, Chapman and Hall/CRC, 2001. pp. 341-361.

Daniel W. 2008. Evolutionary Computation in Java. Retrieved from http://watchmaker .uncommons.org/manual/ ch01s02. Html.

Dass M., Ali M. and Ali M. 2014, March. Image Retrieval Using Interactive Genetic Algorithm. In: Computational Science and Computational Intelligence (CSCI), 2014 IEEE International Conference on. 1: 215-220.

El-Regaily S., El-Messiry H., El-Aziz M and Roushdy M. I. 2012. C21. Single image motion deblurring using Genetic Algorithms. In: Radio Science Conference (NRSC), 2012 29th National. pp. 325-333. IEEE.

Farooq U., Ting-Zhi S., San-Yuan Z and Imran M. 2012. Image Restoration by Using New AGA Optimized BPNN. Procedia Engineering. 29: 3028-3032.

Forrest Stephanie. 1993. Genetic algorithms: principles of natural selection applied to computation. Science. 261: 872-878.

Gonzalez R. and Woods R. 2002. Digital image processing.

Hardie R., Barnard K. and Armstrong E. 1997. Joint MAP registration and high-resolution image estimation using a sequence of under sampled images. Image Processing, IEEE Transactions on. 6(12): 1621-1633.

Haupt R and Haupt E. 1998. Practical Genetic Algorithms. John Wiley and Sons.

He H and Kondi L. 2003. MAP based resolution enhancement of video sequences using a Huber-Markov random field image prior model. In: Image Processing. ICIP 2003. Proceedings. International Conference on. 2: II-933. IEEE.

Hermadi I., Lokan C and Sarker R. 2010. Genetic algorithm based path testing: Challenges and key parameters. In Software Engineering (WCSE), Second World Congress on. 2: 241-244. IEEE.

Holland J. 1992. Genetic algorithms. Scientific American, July, pp. 66-72.

Jaya A., Hashim Z., Haron H., Razali M and Rahman N. 2013. Predictive Modeling of TiN Coatings Grain Size Using RSMc Australian Journal of Basic and Applied Sciences.

Jiang T. 2000. 3D MR image restoration by combining local genetic algorithm with adaptive pre-conditioning IEEE 15th International Conference on Pattern Recognition. 3: 298-301.

Kabán A. and Ali Pitchay S. 2012. Single-frame Image Recovery using a Pearson type VII MRF. Neurocomputing. 80: 111-118.

Khurana N., Rathi A and Akshatha P. 2011. Genetic Algorithm: A Search of Complex Spaces. International Journal of Computer Applications. 25(7): 13-17.

Koza J., Forest B., David Andre and Martin Keane. 1999. Genetic Programming III: Darwinian Invention and Problem Solving. Morgan Kaufmann Publishers.

Li K and Yang Z. 2013. Exemplar Image Completion Based on Evolutionary Algorithms. In: Emerging Intelligent Data and Web Technologies (EIDWT). September, Fourth International Conference on. pp. 696-701. IEEE.

Lin J., Horiuchi T., Hirai and Tominaga S. 2014. Color image recovery system from printed gray image. In Image Analysis and Interpretation (SSIAI), 2014 IEEE Southwest Symposium on. pp. 41-44.

Lin Z. 2012. Image adaptive recovery based on compressive sensing and genetic algorithm. In Computer Science and Automation Engineering (CSAE), 2012 IEEE International Conference on. 2: 346-349.

Lukac R., Plataniotis K., Smolka B and Vene-tsanopulos A. 2004. Color image filtering and enhancement based on genetic algorithm. Proceedings of the inter-national symposium on circuits and systems, ISCAS ’04. 3: 913.

Mahmood A., Dony R and Areibi S. 2013. An adaptive encryption based genetic algorithms for medical images.

In: Machine Learning for Signal Processing (MLSP), 2013 IEEE International Workshop on. pp. 1-6.

Mitchell M. 1998. An Introduction to Genetic Algorithms. MIT Press.

Mukhopadhyay S and Mandal J. 2013. Wavelet based Denoising of Medical Images Using Sub-band Adaptive Thresholding through Genetic Algorithm. Procedia Technology. 10: 680-689.

Papadopoulos G. and Wiggins G. 1998. A genetic algorithm for the generation of jazz melodies. Proceedings of STEP. 98.

Paulinas M and Ušinskas A. 2007. A survey of genetic algorithms applications for image enhancement and segmentation. Information Technology and contro. 36(3): 278-284.

Shimodaira H. 2000. Optimization of Image Processing by Genetic and Evolutionary Computation: How to Realize Still Better Performance. Optimization. 13: 33.

Shimomukai T., Yoshioka M and Yanagimoto H. 2011. Estimation of PSF for a Shaking Blurred Image Using GA. In Machine Learning and Applications and Workshops (ICMLA), 2011 10th International Conference on. 2: 342-345. IEEE.

Snyers D. and Pétillot Y. 1995. Image processing optimization by genetic algorithm with a new coding scheme. Pattern Recognition Letters. 16(8): 843-848.

Srinivas M and Patnaik L. 1994. Genetic algorithms: A survey Computer. 27(6): 17-26.

Sun T and Wu X. 2010. Image restoration based on parallel GA and hopfield NN. In: Distributed Computing and Applications to Business Engineering and Science (DCABES), 2010 9th International Symposium on. pp. 565-567. IEEE.

Suthaharan S., Zhang Z and Sathananthan S. 1997. An improved Wiener filter using genetic algorithm. In Genetic Algorithms in Engineering Systems: Innovations and Applications. GALESIA 97. 2nd International Conference on (Conf. Publ. No. 446). pp. 75-78. IET.

Tippabhatla S. 1998. Processing an image using genetic algorithms technique.

Toledo C., de Oliveira L., Dutra da Silva R and Pedrini H. 2013, June. Image denoising based on genetic algorithm. In: Evolutionary Computation (CEC), 2013 IEEE Congress on. pp. 1294-1301.

Vose and Michael D. 1999. The Simple Genetic Algorithm: Foundations and Theory. MIT Press, Cambridge, MA.

Wang Y. and Fan K. 1996. Applying genetic algorithms on pattern recognition: An analysis and survey. In Pattern Recognition, International Conference on. IEEE Computer Society. 2: 740-740.

Zhang J., Wang K and Shang J. 2012. An Algorithm for Binary Image Restoration. 2012 Spring Congress on Engineering and Technology. 2: 1–4. doi:10.1109/SCET. 2012.6341904.