ISSN (Online) 2393-8021
ISSN (Print) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology
Vol. 2, Issue 4, April 2015

A Survey on Nature Inspired Meta-Heuristics Algorithms in Optimizing the Quantization Table for the JPEG Baseline Algorithm

S.Viswajaa[1] , B.Vinoth Kumar[2], Dr.G.R.Karpagam[3]

PG Student, Department of Computer Science and Engineering, PSG College of Technology, Coimbatore, India[1]

Assistant Professor (Sr.Gr.), Dept.Computer Science and Engineering, PSG College of Technology, Coimbatore, India[2]

Professor, Department of Computer Science and Engineering, PSG College of Technology, Coimbatore, India[3]

Abstract: Images are increasingly displayed at a range of devices linked by scattered networks, which place bandwidth constraints on image transmission. Since imaging has transitioned to digital formats, most favorable settings are needed for image compression. It is feasible to apply lossy JPEG compression to images without compromise of image quality. Quantization table in JPEG decides a degree of compression that reduces the file size significantly, but produces a scale of image distortion that is not vital. Designing of quantization table in JPEG is an optimization problem. For the past decades, numerous research efforts have been concentrated in this particular area. In mid-2000, a new epoch was started, meta-heuristics for solving this problem. Nature inspired algorithms are meta-heuristics that mimic the nature for solving optimization problems. The real beauty of nature inspired algorithms lie in the fact that it receives its sole inspiration from nature. This paper gives an extensive review of some major nature inspired meta-heuristic algorithms such as Genetic Algorithm, Differential Evolution, Particle Swarm Optimization and Firefly Algorithm for optimizing quantization table in JPEG baseline algorithm. Further, key issues involved in solving this problem for these meta-heuristics algorithms are also discussed.

Keywords: Image compression, JPEG, quantization table, optimization problem, Nature inspired algorithms, meta-heuristics algorithms.

I. INTRODUCTION

Image compression is generally used to reduce the size of multimedia without affecting or compromising the originality of it. Image compression is an application of data compression that encodes the original image with fewer bits. Generally, image or digital image suffers from two types of burden redundancy: statistical & psycho-visual. The statistical redundancy implies two types of redundancy. One is spatial due to the correlation or similarity between pixel and its neighbours and the other is coding redundancy in which, the representation of pixel values using fixed length binary coding. On the other hand, the psycho-visual redundancy belongs to the nature of the human eye because the human eye is sensitive to low frequency signal and less sensitive to high frequency information. Human Visual System (HVS) can easily distinguish the changes in edge information about the image but, cannot detect the gray error of the edges.

The main purpose of image compression is to reduce the redundancy of the image which are mentioned above and efficiently store or transmit the data. Image compression can be lossy or lossless.

In lossless compression, when the image is decompressed, there is no loss of information and also the resulting image is identical to the original one. Lossy compression algorithms result in loss of data and the decompressed image is not exactly identical to the original one but close to it.But the lossy compression technique provides a higher compression ratio than lossless compression. Hence lossy compression technique is preferred in many applications, though the quality of the compressed image is not good.

JPEG is one of the most widely used lossy compression technique. In JPEG, it is possible to compress the image without compromising the quality of the decoded image. Quantization table in JPEG decides a degree of compression. Default quantization tables cannot provide the best performance for all application domains. Hence the design of the quantization table is viewed as an optimization problem.

Solving the real-world optimization problems is a challenging task; also many applications have to deal with NP-hard problems. Hence, to solve such problems, optimization tools have to be used, though there is no guarantee that the optimal solution can be obtained. There are no efficient algorithms to solve NP problems. As a result, many problems have to be solved by trial and errors using various optimization techniques. Numerous research efforts have been concentrated in this particular area. Meta-heuristics are widely recognized as efficient approaches for many hard optimization problems. Nature inspired algorithms are meta-heuristics that mimic the nature for solving optimization problems.

This paper provides a detailed review of some major nature inspired meta-heuristic algorithms such as Genetic Algorithm (GA), Differential Evolution (DE), Particle

 DOI 10.17148/IARJSET.2015.2427

Swarm Optimization (PSO) and Firefly Algorithm (FA) for optimizing quantization table in the JPEG baseline algorithm.

Therefore the rest of the paper is organized as follows: section II provides the detailed description of JPEG Baseline Scheme. Section III describes a brief review of some major nature inspired meta-heuristic algorithms such as GA, DE, PSO and FA. Section IV provides analysis of these algorithms in optimizing quantization table.

II. JPEG

JPEG is the acronym for Joint Photographic Experts Group, which is the first international digital image compression standard for continuous-tone still images, both gray scale and color [1]. The JPEG standard defines two vital compression methods. One is Discrete Cosine Transform (DCT) based compression technique and another is the Predictive compression technique. The DCT-Based compression technique is known as JPEG Baseline.JPEG is a lossy format that exploits the properties of human vision to eradicate information that is tricky to differentiate.

JPEG have the subsequent mode of operations:

(a) **Lossless mode:** Lossless mode of encoding follows a simple predictive coding mechanism. This technique does not use 8x8block structure. Based on three adjacent pixels, each pixel is predicted. The predicted pixel is encoded by the use of an entropy encoder.

(b) **Sequential mode:** Sequential method compresses each image in a single scan from left-to-right and from top-to-bottom. It encodes and decodes entire 8x8 blocks by full precision one at a time also supports interleaving of colour components.

(c) **Progressive mode:** Unlike sequential encoding, this technique compresses the image in multiple scans rather than in a single one. When the transmission period is long, the image will be displayed from unclear to clear appearance.

(d) **Hierarchical mode:** This method compresses the image at several resolutions. As a result, the worse resolution of the image can be accessed first with no decompression in the entire resolution of the image.

The last three DCT-based methods namely sequential mode, progressive mode and hierarchical mode are lossy compression because precision restricted to calculate DCT and the quantization procedure bring distortion in the reconstructed image. The lossless approach uses predictive method and does not contain quantization procedure. The baseline JPEG scheme, which is the most extensively used image compression formats in the digital camera, is based on sequential mode.

The main steps to be followed in baseline JPEG image compression [29], [30] are as follows:

1. Import the image.
2. The image is broken into blocks of 8x8 pixels.
3. Apply a DCT to each block from left to right and from top to bottom.
4. Quantize each block of DCT coefficients.
5. Encode the resulting coefficients using a popular encoding scheme known as Huffman encoding.

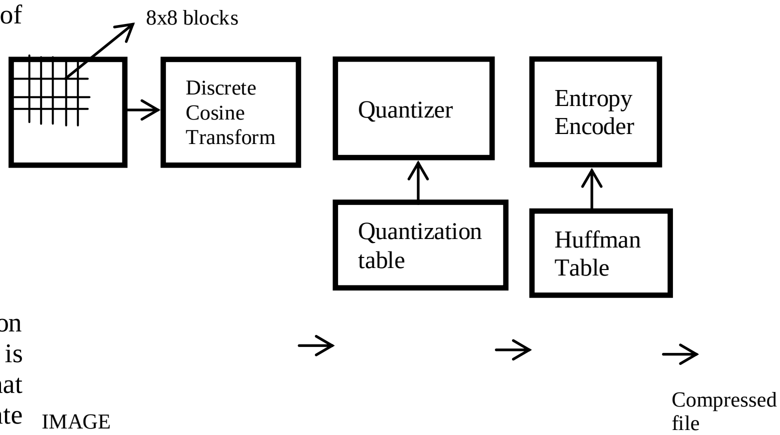

Fig 1. JPEG CODER

The detailed description of each block as shown in Fig 1 is explained below.

A. DISCRETE COSINE TRANSFORM

The image is separated into 8×8 blocks of pixels because compressing an entire image would not yield an optimal result. In the original image if the width or height is not divisible by 8, then the encoder has to make it divisible. The 8×8 blocks are dealt from left-to-right as well as from top-to-bottom. An 8x8 block of pixels can be viewed as a vector in a 64 dimensional space. Each of these blocks is transformed separately. The 64 pixel values are transformed via the Forward Discrete Cosine Transform (FDCT) to 64 coefficients. Hence DCT transforms the image data from the pixel value to the coefficient value.

Mathematical definition of Forward DCT is given by the equation (1).

$$F(u,v) = \frac{1}{4}\, c(u)c(v) \sum_{x=0}^{7}\sum_{y=0}^{7} f(x,y) \cos\left[\frac{\pi(2x+1)u}{16}\right] \cos\left[\frac{\pi(2y+1)v}{16}\right] \qquad \text{..........} (1)$$

For u=0,…,7 and v=0,….,7

The term *F* (*u*, *v*) is known as DCT coefficient.

B. QUANTIZATION

Quantization procedure plays the key role in the JPEG compression. The quality loss in JPEG coding occurs completely in quantization, and much of the compression is gained by run length coding of coefficients with quantization to zero. As a result the quantization table is central to the compression/ quality performance of JPEG

ISSN (Online) 2393-8021
ISSN (Print) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Vol. 2, Issue 4, April 2015

coding. The quantization process removes the high frequencies present in the original image.

After taking the DCT, quantization is applied to 8x8 block. The purpose of the quantization step is to discard information that is not visibly significant. This method is done by basically dividing each component in the frequency domain by a constant for that component and then rounding to the nearest integer value. The quantization matrix is divided by the corresponding quantizer step-size parameter Q(u, v)and it is rounded to the nearest integer as given in equation (2).

$$F_q(u,v) = \text{Round}\left(\frac{F(u,v)}{Q(u,v)}\right) \ldots\ldots\ldots (2)$$

Each element of the quantization table can be any integer value. This value specifies the step size of the quantizer for its corresponding DCT coefficient. A step size of one means no loss for the corresponding coefficient. The larger the value of an element of the quantization table, fewer is the bits of precision used in the corresponding coefficient.

16	11	10	16	24	40	51	61
12	12	14	19	26	58	60	55
14	13	16	24	40	57	69	56
14	17	22	29	51	87	80	62
18	22	37	56	68	109	103	77
24	35	55	64	81	104	113	92
49	64	78	87	103	121	120	101
72	92	95	98	112	100	103	99

Table 1. Luminance quantization matrix

17	18	24	47	99	99	99	99
18	21	26	66	99	99	99	99
24	26	56	99	99	99	99	99
47	66	99	99	99	99	99	99
99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99

Table 2. Chrominance quantization matrix

The JPEG standard does not describe any fixed quantization matrix. It is the privilege of the user to choose a quantization matrix. Two standard quantization matrices for luminance and chrominance component of the JPEG standard are provided in Annex K for reference are shown in Tables 1 and 2 respectively.

C. ENTROPY ENCODER

The final stage in the compression process is entropy encoding. Entropy encoding may be considered as a two-step process. The first step converts the zig-zag sequence of quantized coefficients into an intermediate sequence of symbols. The second step converts these symbols to a data stream in which the symbols no longer have externally identifiable boundaries. The intermediate symbols are generated by performing run length encoding on the quantized DCT coefficients. Here, each non-zero AC coefficient is represented in combination with the run length of zero valued AC coefficients which precede it in the zig-zag sequence.

Entropy encoding achieves additional lossless compression by encoding the quantized DCT coefficients more compactly based on their statistical characteristics. The JPEG proposal specifies two entropy encoding methods, Huffman coding and arithmetic coding. Baseline JPEG code use Huffman coding. It is the technique to produce the shortest possible average code length of the source symbol set and the probability of occurrence of the symbols. By means of these probability values, a set of Huffman code of the symbols can be generated by Huffman Tree. After that, to find the average bit length of DC and AC coefficients, the average bit length score is calculated.

D. DECOMPRESSION

Decompression is accomplished by reversing each of the preceding steps. Initially the compressed image data is decoded by using Huffman decoding. Next step is to dequantize the quantized DCT coefficient values. Inverse DCT (IDCT) is applied by using equation (3) on the quantized coefficients which results in the decompressed image.

Mathematical definition of Inverse DCT is given by equation (3).

$$F(x,y) = \frac{1}{4}\sum_{u=0}^{7}\sum_{v=0}^{7} c(u)c(v)f(u,v)\cos\left[\frac{\pi(2x+1)u}{16}\right]\cos\left[\frac{\pi(2y+1)v}{16}\right] \ldots\ldots\ldots\ldots\ldots (3)$$

For x=0,…,7 and y=0,….,7

III.NATURE INSPIRED ALGORITHM

Optimization is a commonly encountered mathematical problem in all engineering disciplines. It literally means finding the best desirable solution. Regrettably, no particular optimization algorithm exists that can be applied efficiently to all sorts of problems. The process selected for any particular case will depend mainly on the nature of the objective function, the nature of the constraints and the quantity of independent and dependent variables.

Several difficulties such as multi-modality, dimensionality and differentiability are related with the optimization of major problems. Conventional practices such as steepest decent, linear programming and dynamic programming usually not succeeded in resolving such large-scale problems particularly with nonlinear objective functions. Most of the conventional methods need gradient

ISSN (Online) 2393-8021
ISSN (Print) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Vol. 2, Issue 4, April 2015

information and hence it is not potential to resolve non-differentiable function with the help of such conventional methods. Furthermore, such methods frequently fail to resolve optimization problems that have several local optima.

To overcome these problems, there is a need to develop more powerful optimization methods. Hence a new epoch, meta-heuristics was started for resolving these problems. Meta-heuristic is an algorithm proposed to resolve approximately an extensive range of hard optimization problems without having to extremely alter to every problem. A trivial location for the classification of meta-heuristics is to take into account their unique source of inspiration. The majority of the meta-heuristics algorithms are nature inspired.

Nature inspired algorithms are probabilistic exploration methods which simulates the natural evolution or the performance of the natural entities. These algorithms are used especially to discover a most favorable solution for different optimization problems, because they produce finest solutions. Genetic Algorithm (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO) and Firefly algorithm (FA) are some examples of them. They are effectively applied to various optimization problems.

A. GENETIC ALGORITHM

Genetic Algorithm was introduced by Holland. It is a meta-heuristic search technique, which works with the theory of Darwin's assumption of natural evolution [12]. GA is a focused random search process that relies on the working of natural selection and breeding to efficiently discover a huge space of candidate designs and discover optimum solutions.

GA based on real number representation is called Real-Coded Genetic Algorithms. It is natural to represent the genes directly as real numbers for optimization problems of parameters with the variables in continuous domains. Using real coding the representation of the solutions is very close to the natural formulation of many problems. Thus, the coding and decoding processes that are needed in the Binary Coded Genetic Algorithms are avoided, thus increasing the speed. The most accepted genetic operators are selection, crossover and mutation.

The selection method implements the natural selection or the survival-of-the fittest principle as well as choosing good individuals out of the existing population intended for generating the next population according to the assigned fitness. After selection, crossover and mutation recombines and modifies parts of the individuals to create new solutions.

Crossover, also described as the recombination operator, exchanges parts of solutions from two or more individuals, called the parents, and unites these parts to produce new individuals, called children, by means of a crossover probability. There are a lot of ways to employ a recombination operator. The familiar crossover operators comprise one-point crossover.

The role of mutation is to restore lost or unexpected genetic material into a population which prevents the premature convergence of the GA. Mutation frequently modifies some pieces of individuals to form perturbed solutions. Mutation works on a single individual.

The pseudo code for standard GA is illustrated in the algorithm 1 which is adopted from [26].

Algorithm 1. Genetic Algorithm - Pseudo code

```
Begin
Initialise population of chromosomes randomly;
Evaluate the chromosomes;
While maximum generation not reached do
Select superior chromosomes;
Perform single point crossover on selected chromosomes;
Evaluate the offspring;
Append offspring with current population;
Select superior chromosomes;
Perform mutation on selected chromosomes;
Evaluate the offspring;
Append offspring with current population;
End while
Return best chromosome;
End
```

B. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization is a population-based stochastic approach for solving continuous and discrete optimization problems [14].

PSO is initialized with a collection of random solutions and then searches for optima by updating generations. In each iteration, each particle is updated by following two "best" values. The first one is the best solution, it has achieved so far. This value is named as 'pBest'. An additional "best" value that is followed by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and named as 'gBest'. When a particle takes part of the population as its topological neighbours, the best value is a local best and is called 'lBest'.The particle swarm optimization model consists of, at each step, altering the velocity of every particle toward its 'pBest' and'gBest' positions.

The two key operations in PSO are the update of velocity and the update of position. The velocity is updated based on three components: the old velocity, experience of an individual particle and experience of the whole swarm. The updates of the particles in PSO are accomplished by the following equations (4) and (5).

$$V_{i+1} = w^* V_i + c_1 * r_1 * (pBest_i - X_i) + c_2 * r_2 * (gBest_i - X_i) \quad \text{..........} (4)$$

ISSN (Online) 2393-8021
ISSN (Print) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Vol. 2, Issue 4, April 2015

$$X_{i+1} = X_i + V_{i+1} \quad(5)$$

The PSO algorithm does not need complicated encoding and decoding process and particular genetic operator. Inside PSO algorithm, the evolution appears merely for the best solution and all particles are apt to unite to the best solution. The overall process of PSO algorithm is explained in the algorithm 2.

Algorithm 2. Particle Swarm Optimization - Pseudo code

```
Begin
    Generate random population of N particles
    For each individual i, calculate fitness (i);
    Initialize the value of the weight factor
   While maximum generation not reached do
        For each particle do
Set pBest as the best position of particle i;
If fitness (i) is better than pBest;
   Then pBest (i) is the fitness (i);
End if
Set gBest as the best fitness of all particles;
For each particle do
        Calculate particle velocity
        Update particle position
End for
        End for
End while
Update the value of the weight factor
 End
```

C. DIFFERENTIAL EVOLUTION

Another paradigm in the Evolutionary Algorithm family is Differential Evolution which was first proposed by Storn and Price for global optimization over continuous search space. DE is a population based stochastic search technique that enhances a problem by iteratively trying to improve a candidate solution with respect to a given measure of quality.

The implementation process in DE algorithms includes initialization, mutation, crossover and selection. This process is illustrated in algorithm 3 which is adopted from [26]

Algorithm 3. Differential Evolution - Pseudo code

```
Begin
Initialise population of chromosomes randomly;
Evaluate the chromosomes;
While maximum generation not reached do
For all chromosomes do
Select the target chromosome;
Choose three chromosomes in the population randomly;
Compute the mutant chromosome;
Perform crossover between the target and mutant
chromosomes to form trial chromosome;
Evaluate the trial chromosome;
  Replace target chromosome by trial chromosome if
unfitness value of trial chromosome is smaller than target
chromosome;
 End for
End while
Return best chromosome
End
```

The DE algorithm starts by means of a set of random population, which consist the primary explanation for the problem. Mutant vector is created from three different randomly selected targeted vectors. New trial vector is obtained from the target vector and the mutant vector based on the crossover probability. Trial vector and the current target vector are compared and the best out of them forwards to the next generation.

D. FIREFLY ALGORITHM

Firefly algorithm was developed by Xin-She Yang of Cambridge University, which is a nature-inspired meta-heuristic optimization algorithm [15]. Firefly is inspired by the flashing behavior used by fireflies to attract each other in the reproducing procedure.

The brightness of the firefly is the key concept of the algorithm, and is equal to the objective function under consideration. Firefly algorithm is based upon idealizing the flashing characteristic of fireflies [16].
Three fundamental rules were used in the algorithm:

i) All fireflies are unisexual so that is one firefly will be attracted by all other fireflies.

ii) Attraction is dependent on the amount of brightness, that is a less brighter firefly gets attracted to a brighter one. If there is no brighter one than a specific firefly, it will move randomly.

iii) The brightness of the firefly is equal to the objective function.

The attractiveness is dependent on the distance between the two fireflies as the intensity of light decreases as the distance between the two firefly's increases. Therefore, the closer the fireflies the more attractive they seem to each other.

The Parameters involved in the firefly algorithm:

(i) Distance among the fireflies

Distance among firefly i and j are well-defined by Cartesian distance is shown in equation (6).

$$r_{ij} = | x_i - x_j | = \Sigma_{k=1}^{d} (x_{i,k} - x_{j,k})^2 \quad(6)$$

(ii) Relative Brightness

ISSN (Online) 2393-8021
ISSN (Print) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Vol. 2, Issue 4, April 2015

Brightness of a single firefly at spot x is signified by I, and its comparative brightness is calculated by using equation (7)

$$I=I_o \times e^{-\gamma r_{ij}} .... (7)$$

Where I_0 is its initial brightness, specifically brightness at r=0. γ signifies the grade of light attenuation.

(iii) Degrees of Attraction

Degrees of attraction can be produced with the subsequent equation (8)

$$\beta = \beta_o \times e^{-\gamma r_{ij}^2} .... (8)$$

Where β_0 is the main grade of attraction, specifically the degree of attraction at r= 0.

(iv) Position Update

Position update once firefly is attracted to the brighter one j, which is specified by equation (9).

$$X_i= X_i + \beta_o \times e^{-\gamma r_{ij}^2} (x_j-x_i) + \alpha\,(rand -1/2) .... (9)$$

Where $\beta_o \times e^{-\gamma r_{ij}^2} (x_j-x_i)$ is the attraction of firefly j to firefly i. α is the step factor which is a random number in the series of [0, 1], and rand is a random number consistently distributed in the series of [0, 1].

The overall process of firefly algorithm is described in algorithm 4.

Algorithm 4. Firefly Algorithm - Pseudo code for

```
Begin
Initialize population of fireflies randomly
While maximum generations not reached do
For firefly i=1: n
    For firefly j=1: i
      Determine Light intensity, Ii
      If Ii is greater than Ij
        Move firefly i towards j in all dimensions
          Else
        Move firefly i randomly
      End If
     Attractiveness changes with distance r
     Determine new solutions and revise light intensity
End for j
End for i
End while
Sort the fireflies
Return the current best
End
```

IV. DISCUSSION

Considering all the Nature inspired algorithms, it is clear that the following specific steps are in common.

1. Initialization
2. Fitness function (Objective function)
3. Selection
4. Exploitation
5. Exploration

A. *INITIALIZATION*

In Nature inspired algorithms, initialization is a critical task as it can affect the convergence speed and also the quality of the concluding result.

Designing the quantization table in the JPEG is the aim of this paper. The general structure of quantization table is an 8x8 matrix. Each individual element in the matrix is characterized according to the algorithms used. For example, in GA each element in the matrix is represented as genes and in PSO, each element is represented as particles. Similarly, in FA it is represented as fireflies.

A survey on initialization process in some of the nature inspired algorithms is given below.

In [17] Hanli Wang and Sam Kwong, describes about the two quantization tables namely luminance and chrominance. Each quantization table is represented as chromosomes. Since the quantization table is an 8x8 matrix in which all chromosomes has 64 genes, there are completely 128 genes. Each gene signifies an individual element in the quantization table. For the initial chromosomes, their genes are produced randomly under the restriction as mentioned in the equation (10)

$$1 \le g_i \le G_{max} ,\ 0 \le i \le 127 ....(10)$$

where $g_i$is the integer value of the *i*th gene, and $G_{max}$is a predefined integer which determines the maximum value for the genes.

In the reference [18], Yung-Gi Wu also represents each quantization table as a chromosome. A random number generator is used which produces the initial chromosomes. Rand () function is used to generate every chromosome. Since quantization is a division operation and rand () % W creates a random number from zero to W-1, W is set to 512 for simulation. While the JPEG default quantization is given as input to one of the initial chromosomes which speeds up the unfitness value reduction.

In the reference [19], a natural image is selected; an 8x8 block of 8-bit samples is extracted. Quantization Tables are produced by a random process.

In this paper the population is assumed as 16. Hence the program creates 16 Quantization Tables as an initial population, which denotes a collection of 16 Tables competing to be the expected Quantization Table that will be given to the action of crossover and Mutation.Though the coefficients of the quantization tables are random, they also must have their values adjusted with a similar characteristic to the JPEG Standard Table.

ISSN (Online) 2393-8021
ISSN (Print) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Vol. 2, Issue 4, April 2015

In the reference [20] at the beginning of executing algorithm, the number of initial population is defined as 64. And the image is divided into small plots of an 8x8 pixel matrix. The pixel matrix block is transformed by Discrete Cosine Transform and then it is encoded, transmitted and decompressed.

Each 8 × 8 chromosome is divided into four 4 × 4 sub tables. Though the genes are generated randomly, the ranges of values used in the sub table are derived from the standard JPEG tables. Hence, in the reference [21] the knowledge is contributed towards a better initial population.

In the reference work [22] the genes are defined as integer's ranges from [1,255].

The first process in PSO is also initialization. In the initialization process, the initial swarm of particles is generated. Each particle is initialized with a random position and velocity [24].

In the DE algorithm, the solution space is represented by a D- dimensional vector. The values in the D-dimensional space are commonly represented as real numbers. The initialization process is done by randomly generating the initial population of size N of D- dimensional vectors [27].

In the reference work [26], the author represents the genes in the chromosome within the range of 1 to 256.

Similar to all other algorithms**,** Firefly algorithm also randomly generates the population. In the reference work [25], the author initially generates the fireflies randomly where i vary from one to finite.

From all these references it is inferred that the structure of the quantization matrix is an 8x8 block. The value in the matrix ranges from either 1 to 256 or 1 to 512. And if the JPEG standard quantization tables are put into the initial population as single chromosome, the processing time is reduced to achieve optimal solution.

B. FITNESS FUNCTION

The survival probability of all chromosomes is evaluated with the help of the fitness function. It is considered to be an objective function. There are several quality metrics available which are used as the fitness function.

In the reference [17], Compression ratio and Peak Signal to Noise Ratio (PSNR) are used as the evaluation function.

The compression ratio (CR) is given by equation (11), which is the number of bits required to represent the image before compression to the number of bits required to represent the image after compression.

$$CR = 100.\,(1 - JPEGSize/original\ Size) \quad \ldots\ldots\ldots\ (11)$$

PSNR is a measure of the peak error which is given by the equation (12).

$$PSNR = 20 * \log10\,(255 / \mathrm{sqrt}\,(MSE)) \quad \ldots\ldots\ldots\ (12)$$

In this reference it is assumed that users are more interested to get a higher image quality for a given compression ratio. So the first priority is given to the compression ratio and the second priority is to set the PSNR value.

In the reference work [19], the maximum value of Signal to Noise Ratio (SNR), which is defined as the ratio of signal power to the noise power corrupting the signal, is the fitness function which specifies the quality of each string.

In the paper [20] the fitness function is described in the equation (13)

$$f = 1/1 + GCV\,(\delta) \quad \ldots\ldots\ldots\ (13)$$

The equation (14) gives the formula of GCV (δ) which is used in the fitness function.

$$GCV\,(\delta) = (N.\,\|W - W_\delta\|^2)/N_0^{\,2} \quad \ldots\ldots\ldots\ (14)$$

In the above equation, N_0 is the number of zero, which is set by DCT coefficient; Nis the total number of DCT coefficients; W_δ represents the vector of DCT coefficient after selecting the threshold; W represents the raw vector of DCT coefficient.

In the reference [21] instead of fitness functions, unfitness function is used. The unfitness function is similar to the standard optimization formulation for rate distortion optimization. An unfitness function (ξ) is defined by the following equation (15)

$$\xi = a\,(8/B_r - \lambda)^2 + \varepsilon \quad \ldots\ldots\ldots (15)$$

Where B_r is the bit rate of each chromosome; λ is the desired compression ratio; ε represents the MSE of the decoded image;

In the reference work [22] each chromosome is related with a vector of two elements, where both elements expressed the fulfilment degree of the two objectives. The first element measures the compression ratio (CR) defined as in equation (11)

Another element of the vector measures the image quality through the mean squared error (MSE) given in equation (16) which measures the average of the square of the error.

$$MSE\,(X, X') = \frac{1}{M.N}\,.\sum_{i=1}^{N}\sum_{j=1}^{M}(Xij - Xij')2 \quad \ldots\ldots\ldots\ (16)$$

In PSO, after the initialization process, each particle is evaluated based on the fitness function. In the reference work [23] each particle is related to two vector elements.

The first element measures the compression ratio as mentioned in the equation (11) and another element measures the image quality by using MSE which is defined by the equation (16).

In the work [25], the author considers the brightness of the firefly as similar to the fitness function.

For DE algorithm, in the work [26], the author uses the same unfitness function as in equation (15) to evaluate the chromosomes.

C. SELECTION

Selection is a mechanism for selecting individuals from a population according to their fitness function. The fitness of an individual is evaluated. The highest rank chromosome will have more possibility of selection and the worst will be eliminated.

Some well-known selection methods are: Roulette wheel selection, Tournament selection, Rank selection, Steady state selection and so on.

Roulette wheel selection is used in the work [18] which describes about the designing of the quantization table for medical images by GA.

In the work [19], initially a random number is drawn to make sure which string will be selected during the natural selection. This occurs another time to decide on the other string to produce a couple of strings of 16 bits each one selected by the roulette wheel.

In the paper [20] roulette wheel selection is employed according to the uniform random number in the interval of [0, 1].

In the reference [21] an intermediate deterministic approach is introduced in the parent selection in order to avoid premature convergence. Based on the crossover probability, chromosomes which have good unfitness values are selected. Chromosomes, which produce better decoded image quality, are selected as parents for crossover.

From all the above references it is inferred that roulette wheel selection is mostly employed for all kinds of problems which uses Genetic Algorithm.

The selection in PSO is explained below which is mentioned in the reference [27] : Each time a fitness value is calculated, it is compared against the previous best fitness value of the particle and the previous best fitness value of the whole swarm, and the personal best and global best positions are updated by the equations 5 and 6. If a stopping criterion is not met, the velocity and position are updated to create a new swarm. The personal best and global best positions, as well as the old velocity, are used in the velocity update.

In DE, the selection process is done by comparing the current target chromosome with the trail chromosome. In the work [26], the trail chromosome $U_{i,G}$ is evaluated using the fitness function. If the fitness value of the trail chromosome is lower than that the target chromosome $X_{i,G}$ then the target chromosome is replaced with the trail chromosome otherwise the target chromosome is continued in the next generation.

D. EXPLOITATION

Exploitation is needed to identify parts of the search space with high quality solutions. Exploitation is important to intensify the search in some promising areas of the accumulated search experience.

After the selection process, crossover is applied. A Crossover is a recombination operator that combines subparts of two parent chromosomes to produce offspring that contains some parts of both parents. In the crossover, highly fit individuals are given opportunities to reproduce by exchanging pieces of their genetic information. This produces new "offspring" solutions, which share some good characteristics taken from both parents. There are several types of crossover is available among that the commonly used single point crossover operator is performed by randomly selecting a place along the string and by exchanging all bits on the right side of the crossover place.

Offspring chromosomes are produced by exploitation. As far as the crossover is concerned, one-point crossover is familiar one which is used in many applications. In the reference [17] the crossover process arbitrarily chooses a cut-off point. Crossover probability (p_c) with a value between 0.6 and 1.0 is generally used.

In the paper [18], crossover works on adjacent chromosomes and switches genes amongst these two chromosomes. After that, each crossover operator yields two offspring. The numbers and positions of genes together to be swapped among two chromosomes are decided arbitrarily.

In the reference work [19],when the new population is created from the selection procedure, additional random number (P_{cruz}) is drawn to the range [0, 1]. The P_x is the crossover rate. If P_{cruz} is equal to the P_x, crossover is applied. The place which happens exchanging of the bits is selected by a random process.

In the reference [21] single point crossover is employed. From the positions 2 to 25 in the chromosomes, the crossover point is selected randomly. During the quantization process, top left sub table interacts with lower order DCT coefficients which play an important role in the quality of the block. Hence the position is chosen randomly from 2 to 25.

In the work [22], the author applies classical one-point crossover. The one-point crossover operator cuts two

IARJSET

ISSN (Online) 2393-8021
ISSN (Print) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology
Vol. 2, Issue 4, April 2015

chromosomes at some chosen common gene and switches the resultant sub-chromosomes. The common gene is selected by extracting arbitrarily a number in the range [1, 64].

The exploitation process is referred as the local search in PSO, which is done with the help of the parameters C_1 and r_1 in the equation (17).

$$V_{i+1} = w^* V_i + c_1 * r_1 * (pBest_i - X_i) + c_2 * r_2 * (gBest_i - X_i) \quad \text{.............} \quad (17)$$

In the reference [24] the parameter C_1 in equation (17) is set to 1.49455. By setting this parameter, the inference gained is that there is a good balance between exploration and exploitation in PSO.

In DE, exploitation is based on crossover. A candidate or target chromosome $X_{i,G}$ from the initial population is considered and crossover is performed between mutant chromosome and target chromosome $X_{i,G}$ to obtain the trial chromosome $U_{i,G}$.

In firefly algorithm, the process of exploitation is based on the movement of the firefly. The parameters x_j and x_i in the equation (18) are responsible for the movement of the firefly.

$$X_i = X_i + \beta_o \text{ x } e^{-\gamma r_{ij}^2} (x_j - x_i) + \alpha \text{ (rand -1/2)} \text{ ………. } (18)$$

In the reference [25] movement of a firefly is given by the above equation which is based upon the attractiveness and when firefly *j* is more attractive (brighter) than firefly *i*, firefly i is moving towards *j*.

E. EXPLORATION

Generation of new solutions in the search space is termed as exploration. The selection and crossover operators will generate a large amount of different off springs.

In the mutation, the offspring can either replace the whole population or replace less fit individuals. Mutation operator changes 1 as 0 and vice versa by bit wise.

In the reference [17], offspring chromosomes are produced by exploration process. The mutation process modifies each bit of the genes with a small probability (p_m) with the value equal to or less than 0.1.

In the work done in [18], once all the chromosomes in the crossover pool have the equal gene patterns over numerous generations; crossover occasionally falls into a local optimization. On the other hand usage of a mutation operator can avoid this localized optimum. Mutation operators are applied to the last few chromosomes whose survival aptitudes are worse after crossover processes. The customized chromosomes are assessed for unfitness value, the chromosomes in the collection are organized once more and the finest chromosomes are taken.

In the paper [19], mutation is applied with a frequency around 0.1, for every string in the population and for each bit within the string produces a random number r which is between 0 and 1.

In the reference [21] exploration operation is based on their rank. According to their unfitness value, rank is assigned to all chromosomes. The chromosomes are divided into 6 groups. The group with least unfitness value is considered as high rank. In this reference work, exploration is done only in the top left, top right and bottom left sub tables. Since the genes in these positions have an impact on the quality of the pixel block.

In the reference [22] the author applies two mutation operators. In the first mutation operator, N genes, with N a random number in [1, 16] are selected at random over the chromosome length and are altered into another possible value for that gene. In another mutation operator, all 64 genes are scaled by using the process of the IJG baseline algorithm with a value of q randomly selected in the interval [1,100].

The exploration process is referred as the global search in PSO. The parameters C_2 and r_2 in the equation (17) are responsible for the exploration process. In the reference [24] the parameter C_2 is also set to 1.49455 which is same as C_1. By setting this parameter, it is inferred that there is a good balance between exploration and exploitation in PSO.

In DE, from the initialization process target vector is created. In the reference work [26] the mutant vector is represented as $V_{i,G}$ which is generated from the randomly selected three vectors $X_{r1,G}$ $X_{r2,G}$ $X_{r3,G}$ is shown in equation (19)

$$V_{i,G} = X_{r1,G} + F(X_{r2,G} - X_{r3,G}) \text{……….} (19)$$

Where the scale factor $F \in (0, 1^+)$ is a positive real number.

In firefly algorithm, the process of exploration is based on the movement of the firefly. The parameter β_0 in the equation (18) is responsible for the exploration process. In the reference work [25], the author sets the value of β_0 as zero as similar to many problems.

V. CONCLUSION

This paper provides a detailed survey on some of the nature inspired meta-heuristics algorithms such as GA, PSO, DE and FA for optimizing the quantization table in JPEG.

A detailed analysis is made on some of the common steps which are in practises such as initialization, selection, fitness function, and exploration and exploitation process. The Quantization table generated using Nature inspired meta-heuristics algorithms work better in compressing the image when compared to the quantization table generated from JPEG.

ISSN (Online) 2393-8021
ISSN (Print) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology
Vol. 2, Issue 4, April 2015

Among the four nature inspired algorithms discussed in this paper, it can be inferred that DE gives better results.

REFERENCES

[1] Gregory K. Wallace, ‘The Jpeg Still Picture Compression Standard’, IEEE Transactions on Consumer Electronics, Vol. 38, No. 1, 1992
[2] Carlos A. Coello, Gary B. Lamont and David A. Van Veldhuizen, ‘Evolutionary Algorithms for Solving Multi-Objective Problems’, Second Edition, Springer, 2007
[3] Satyasai Jagannath Nanda, Ganapati Panda, ‘A survey on nature inspired meta-heuristic algorithms for partitional clustering’, Swarm and Evolutionary Computation 16 (2014)1–18, ELSEVIER, 2014
[4] Ya-Hui Shiao, Tzong-Jer Chen, Keh-Shih Chuang, Cheng-Hsun Lin and Chun-Chao Chuang, ‘Quality of Compressed Medical Images’, Journal of Digital Imaging, Springer, 2007.
[5] Priyanka dixit, Mayanka dixit, ‘Study of JPEG Image Compression Technique Using Discrete Cosine Transformation’, International Journal of Interdisciplinary Research and Innovations (IJIRI) Vol. 1, Issue 1, pp: (32 35), 2013.
[6] Long WC, Ching YW, Shiuh ML, ‘Designing jpeg quantization tables based on human visual system’, Image Processing Conference; 24-28 October 1999; Kobe, Japan. New York, NY, USA: IEEE. pp. 376-380, IEEE 1999
[7] Abu NA, Ernawan F, Suryana N, ‘A generic psycho visual error threshold for the quantization table generation on jpeg image compression’, Signal Processing and its applications Colloquium; 2013; Kuala Lumpur, Malaysia. New York, NY, USA: IEEE. pp. 39-43, IEEE 2013
[8] Jinjian Wu, Guangming Shi, Weisi Lin, Anmin Liu, and Fei Qi, ‘Just Noticeable Difference Estimation for Images with Free-Energy Principle’, IEEE Transactions on Multimedia, VOL. 15, NO. 7, 2013.
[9] Xiaohui Zhang, Weisi Lin, and Ping Xue, ‘Just Noticeable Difference Estimation with Pixels in Images’, Journal of Visual Communication & Image Representation vol. 19, no. 1, 2008.
[10] Chang-Hsing Lee, Pei-Ying Lin, Ling-Hwei Chen, Wei-Kang Wang, ‘Image enhancement approach using the just-noticeable-difference model of the human visual system’, Journal of Electronic Imaging 21(3), 2012
[11] Xin- She Yang, ‘Nature-inspired Metaheuristics Algorithms’, Second Edition, University of Cambridge, United Kingdom, LUNIVER PRESS, 2010.
[12] K. F. Man, K. S. Tang, and S. Kwong, ‘Genetic Algorithms: Concepts and Applications’, IEEE Transactions on Industrial Electronics, VOL. 43, No. 5, 1996
[13] Ziqiang Wang, Xia Sun and Dexian Zhang, ‘A Swarm Intelligence Based Color Image Quantization Algorithm’, 1st International Conference on Bioinformatics and Biomedical Engineering, IEEE, 2007
[14] Qinghai Bai, ‘Analysis of Particle Swarm Optimization Algorithm’, Computer and Information science, VOl.3, No.1, 2010
[15] Iztok Fister, IztokFisterJr, Xin-SheYang, JanezBrest, ‘A comprehensive review of firefly algorithm’, ELSEVIER, 2013.
[16] Sankalap Arora, Satvir Singh, ‘The Firefly Optimization Algorithm: Convergence Analysis and Parameter Selection’, International Journal of Computer Applications (0975 – 8887) Volume 69– No.3, May 2013
[17] Hanli Wang, Sam Kwong, ‘Preferential Multi-Objective Genetic Algorithm for JPEG Quantization Table Optimization’, Proceedings of the Fourth International DCDIS Conference, 2005
[18] Yung-Gi Wu, ‘GA-based DCT quantization table design procedure for medical images’, Vision, image and signal processing, IEEE, 2004.
[19] Leonardo Faria Costa and Antonio Claudio Paschoarelli Veiga, ‘Identification of the best quantization table using Genetic algorithms’, Pacific Rim Conference on Communications, Computers and signal Processing, IEEE, 2005
[20] Chen shuwang, An Tao, Hao litao, ‘ Discrete Cosine Transform Image Compression based on Genetic Algorithm’, International Conference on Information Engineering and Computer Science, IEEE, 2009.
[21] Vinoth Kumar B and Karpagam GR, ‘Knowledge based genetic algorithm approach to quantization table generation for the JPEG baseline algorithm’, Turk. J. Electr. Eng. Co. [In Press]
[22] Beatrice Lazzerini, Francesco Marcelloni, Massimo Vecchio, ‘A multi-objective evolutionary approach to image quality/compression ratio trade-off in jpeg baseline algorithm’, Applied Soft Computing 2010; 10: 548–561, ELSEVIER, 2009
[23] Huizhu Ma, Qiuju Zhang, ‘Research on cultural-based multi-objective particle swarm optimization in image compression quality assessment’, Optik 124 (2013) 957– 961, ELSEVIER, 2012
[24] Kevin J. Binkley, Masafumi Hagiwara, ‘Balancing Exploitation and Exploration in Particle Swarm Optimization: Velocity- based Reinitialization’, Transactions of Japanese Society for Artificial Intelligence 23(1):27-35, 2008
[25] Milan Tuba and Nebojsa Bacanin, ‘JPEG Quantization Tables Selection by the Firefly Algorithm’, International conference on Multimedia Computing and Systems (ICMCS), IEEE, 2014
[26] Vinoth Kumar B and Karpagam GR, ‘Differential evolution versus genetic algorithm in optimising the quantisation table for JPEG baseline algorithm’, International Journal on Advanced Intelligence Paradigms, [In Press]
[27] Voratas Kachitvichyanukul, ‘Comparison of Three Evolutionary Algorithms: GA, PSO, and DE’, Industrial Engineering & Management Systems Vol 11, No 3, September 2012.
[28] Ilhem Boussaid, Julien Lepagnot, Patrick Siarry, ‘A survey on optimization metaheuristics’, Information Sciences 237 (2013) 82–117, ELSEVIER, 2013
[29] Vinoth Kumar B and Karpagam GR. An empirical analysis of requantization errors for recompressed JPEG images. International Journal of Engineering Science and Technology. 2011; 3(12):8519–27.
[30] Vinoth Kumar B, Karpagam GR and Vijaya Rekha N. Performance Analysis of Deterministic Centroid Initialization Method for Partitional Algorithms in Image Block Clustering. Indian Journal of Science and Technology, Vol 8(S7), 63–73, April 2015

BIOGRAPHIES

Viswajaa S obtained her B.E degree in the Department of Electronics and Communication Engineering from PSNA College of Engineering and Technology, Dindigul and currently pursuing her M.E degree in the Department of Computer Science and Engineering from P.S.G. College of Technology, Coimbatore. Her area of interest includes Image processing and Evolutionary Computing.

Vinoth Kumar B is a Senior Grade Assistant Professor with 11 years of experience in the Department of Computer Science and Engineering, PSG College of Technology, Coimbatore. His areas of research include soft computing and digital image processing. He has published his research contributions in peer reviewed international journals and conferences. He has served as a member of the board of studies and reviewer in conferences.

Dr.G.R.Karpagam is a Professor with 18 years of experience in the Department of Computer Science and Engineering, PSG College of Technology, Coimbatore. She is an IEEE member doing her research in the field of web services, evolutionary computing, MDA and cloud. She has published papers in peer reviewed national/international journals and conferences and a reviewer of international journals. She has received research grants from Indian government agencies and has setup IaaS Datacenter for cloud research. She has established industry funded laboratories namely Open-Source Software, SOA and Cloud, in collaboration with leading MNCs.