Chapter 5
Nature Inspired Optimization Techniques for Image Processing—A Short Review

S. R. Jino Ramson, K. Lova Raju, S. Vishnu and Theodoros Anagnostopoulos

Abstract Nature–inspired optimization techniques play an essential role in the field of image processing. It reduces the noise and blurring of images and also improves the image enhancement, image restoration, image segmentation, image edge detections, image generation, image fusion, image pattern recognition, image thresholding and so on. Several optimization techniques have been proposed so far for various applications of image processing. This chapter presents the short review of nature inspired optimization algorithms such as Genetic algorithm, Genetic programming, evolutionary strategies, Grey wolf optimization, Bat optimization, Ant colony optimization, Artificial Bee Colony optimization, Particle swarm optimization, Firefly optimization, Cuckoo Search Algorithm, Elephant Herding optimization, Bumble bees mating, Lion optimization, Water wave optimization, Chemical reaction optimization, Plant optimization, The raven roosting algorithm with the insight of applying optimization algorithms in advanced image processing fields.

Keywords Optimization techniques · Image processing · Short review
Evolutionary algorithms · Swarm intelligence algorithms

5.1 Introduction

Nature inspired optimization techniques play a key function in the field of engineering, business, industrialized designs, image processing and so on. The main objectives of nature inspired optimization technique are to increase the productivity,

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gain, efficiency, accomplishment and so on, and to underrate the energy use, cost, size and so forth. Digital Images are viewed as a group of picture element, and each picture element containing few values to represent visual property, illumination, tone etc. Generally, image processing defines refine/manage/transfer an image. Also, it uses various algorithms to improve the nature of the image, to obtain confidential data. Nature-inspired optimization techniques play [1] an essential role in image processing. It reduces the noise and blurring of images and also improve the image enhancement/image restoration/image segmentation/image edge detections/image generation/image fusion/image pattern recognition/image thresholding.

5.1.1 Nature Inspired Optimization Algorithms

A lot of special approaches were received to perform various works on the image. In recent times various new techniques and algorithms are popularized which are motivated from the nature. The keys which are best surrounded by massive group of solutions are forwarded after formation or after iteration step and inactivity is not needed. The recent algorithms are very effective compared to early Nature Inspired Algorithms. These algorithms have been reached extensive popularity in recent years to handle many tough real world optimization problems. All these comes under the category of meta-heuristics algorithms.

Several nature inspired optimization algorithms have been developed and studied so far. They are, Genetic Algorithm (GA), Simulated annealing (SA), Artificial immune systems (AIS), Boids, Tabu Search, Memetic Algorithm (MA), Ant Colony Optimization Algorithm (ACO), Cultural Algorithms (CA), Particle Swarm Optimization (PSO), Self-propelled Particles, Differential Evolution (DE), Bacterial Foraging Optimization, Harmony Search (HS), Marriage in Honey Bees Optimization (MBO), Artificial Fish School Algorithm, Bacteria Chemotaxis (BC) Algorithm, Social Cognitive Optimization (SCO), Artificial Bee Colony Algorithm, Bees Algorithm, Glowworm Swarm Optimization (GSO), Honey-Bees Mating Optimization (HBMO) Algorithm, Invasive Weed Optimization (IWO), Shuffled Frog Leaping Algorithm (SFLA), Central Force Optimization, Intelligent Water Drops algorithm, River Formation Dynamics, Biogeography-based Optimization (BBO), Roach Infestation Optimization (RIO), Bacterial Evolutionary Algorithm (BEA), Cuckoo Search (CS), Firefly Algorithm (FA), Gravitational Search Algorithm (GSA), Group Search Optimizer, League Championship Algorithm (LCA), Bat Algorithm, Bumble Bees Mating Optimization (BBMO) Algorithm, Eagle Strategy, Fireworks algorithm for optimization, Hunting Search, Altruism Algorithm, Spiral Dynamic Algorithm (SDA), Strawberry Algorithm, Artificial Algae Algorithm (AAA), Bacterial Colony Optimization, Differential Search Algorithm (DS), Flower pollination algorithm (FPA), Krill Herd, Water Cycle Algorithm, Black Holes Algorithm, Cuttlefish Algorithm, Gases Brownian Motion Optimization, Mine blast algorithm, Plant

Propagation Algorithm, Social Spider Optimization (SSO), Spider Monkey Optimization (SMO) algorithm, Animal Migration Optimization (AMO) Algorithm, Artificial Ecosystem Algorithm (AEA), Bird Mating Optimizer, Forest Optimization Algorithm, Golden Ball, Grey Wolf Optimizer, Seed Based Plant Propagation Algorithm, Lion Optimization Algorithm (LOA), Nature-Inspired Meta-heuristic Algorithm, Optics Inspired Optimization (OIO), The Raven Roosting Optimisation Algorithm, Vortex Search Algorithm, Water Wave Optimization, collective animal behavior CAB algorithm, Bumble bees mating optimization (BBMO), Parliamentary optimization algorithm (POA), Artificial Chemical Process Algorithm, Artificial Chemical Reaction Optimization Algorithm, Bull optimization algorithm, Elephant herding optimization (EHO). All the nature inspired optimizations falls under two main classification namely Evolutionary Algorithms and Swarm Intelligence Algorithms. This chapter presents the short review of some Nature-Inspired Optimization Techniques which are efficiently applied for image processing.

5.2 Evolutionary Algorithms

The flow cycle of evolutionary algorithm is shown in Fig. 5.1. The evolutionary algorithms are inspired from biological evolution like reproduction, mutation, recombination, and selection. The optimization technique plays a vital role in estimating accurate solutions or best solutions from a group of solutions. If a group of individual is concerned, each individual will have his own best solution and the global best will be the best among the local best. Evolutionary algorithm achieved victory on many difficult problem solving with the help of fitness function and the stream which is using Evolutionary algorithm as a tool for problem solving is known as Evolutionary Computation. The evolutionary computation is fundamentally based upon the fitness function and improving the fitness function will results in optimal solutions.

5.2.1 Classification of Evolutionary Algorithms

The broad classification of Evolutionary algorithm for image processing is shown in Fig. 5.2.

(a) **Genetic Algorithm (GA)**:

In 1989, Genetic Algorithm (GA) was introduced by D. Goldberg, J. Holl and K. De Jong. Genetic algorithm is a sub-class of evolutionary algorithms which is inspired from the natural selection. This algorithm resembles the operations such as mutation, crossover and selection.

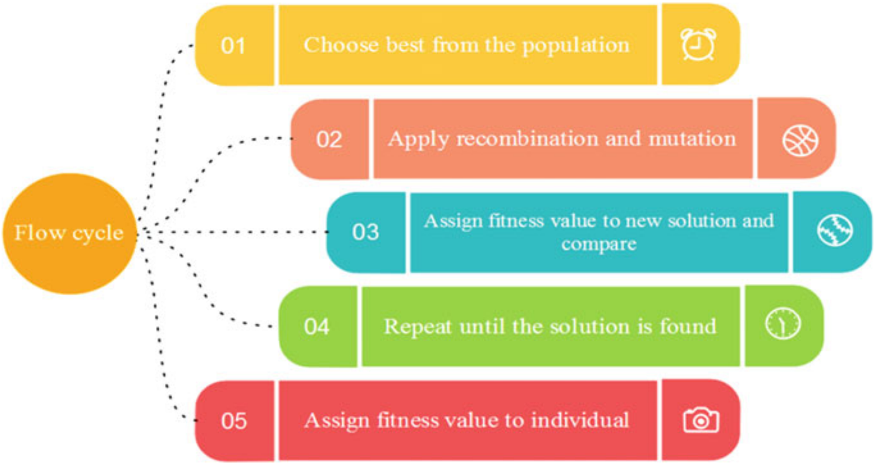


Fig. 5.1 Flow cycle of evolutionary algorithm

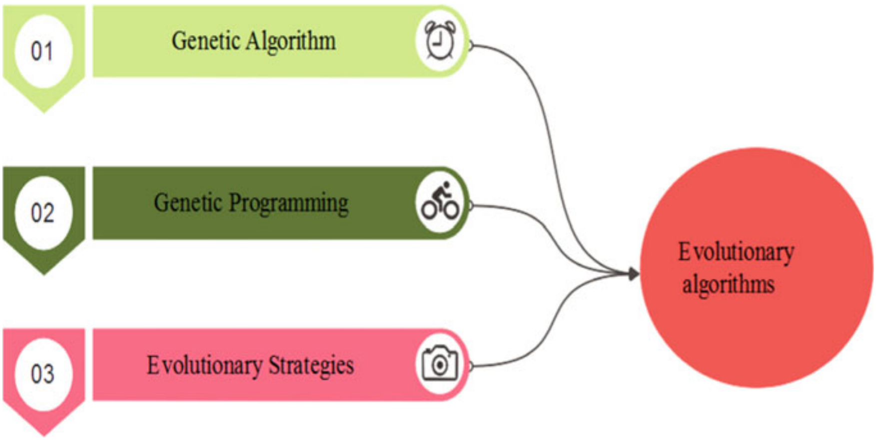


Fig. 5.2 Evolutionary algorithms

GA randomly generates some set of possible solutions to a problem. Each solution is subjected to the fitness function to evaluate each solution. New possible solutions will be generated from the best solutions of the previous step. The process will be continued until the acceptable solution is found. References [2–11] presents the applications of GA in various fields of Image processing and the detailed review is tabulated in Table 5.1.

(b) **Genetic Programming (GP)**:

John Koza has introduced Genetic Programming (GP) in 1992. Genetic programming (GP) is an extension of Genetic Algorithm which is used for testing and

Table 5.1 Review of genetic algorithm

References	Technique used	Applications	Parameters evaluated	System used/software used
Maihami et al. [2]	Genetic-based prototyping	Image annotation	Scale-invariant feature transform and robust hue descriptor	MATLAB programming language in Intel Core i5 CPU 2.4 G and 4 G RAM
Pujari et al. [3]	DNA sequence	Image encryption	–	Matlab
Abbas et al. [4]	Rational ball cubic B-spline representation	Image interpolation	Peak signal to noise ratio (PSNR)	Matlab
Tarigan et al. [5]	Back propagation neural network	Automatic ticketing system for vehicles	Epoch and time (in seconds)	Matlab
Miri et al. [6]	–	Image steganography	Mean square error (MSE), peak signal to noise ratio (PSNR), PSPNR	Matlab
Sukhija et al. [7]	Principal component analysis (PCA)	Face recognition	Number of classes, number of test cases	Matlab
Hung et al. [8]	Parallel fuzzy C-means clustering	MRI segmentation	–	NVIDIA Jetson TK1, Kepler GPU architecture with 192 CUDA cores and 2 GB DDR2 RAM, integrated with an ARM Cortex- A15 CPU with four cores with an Ubuntu Linux Operating System. CUDA version is 6.5
Nagarajan et al. [9]	Diverse density (DD)	Medical image feature extraction	No of cycles, fitness value, probability	Matlab
Zafari et al. [10]	Modified selective computational ghost imaging (SCGI)	Noise filtering	Quality index of the image	Matlab
Sethi et al. [11]	Cryptography	Image hiding	Mean square error (MSE), peak signal to noise ratio (PSNR), capacity	Matlab

Table 5.2 Review of genetic programming

References	Technique used	Application	Parameters evaluated	System/software used
Liang et al. [12]	Support vector machine (SVM)	Figure-ground segmentation	Fitness function, accuracy	Matlab R2014b
Liang et al. [13]	Clustering	Figure-ground segmentation	Mean, variance, skewness, kurtosis, energy, entropy	Matlab R2014b
Iqbal et al. [14]	Transfer learning GP-criptor	Image classification	Kylberg, Brodatz, and Outex data sets	EC Java-based software
Mahmood et al. [15]	Blind image de-convolution	Image acquisition	Root mean square error (RMSE), peak signal to noise ratio (PSNR)	GP simulations are carried out using GPLAB toolbox in MATLAB 7.0

selecting best choice among the set of results. It uses biological evolution to find solutions for complex problems. References [12–15] presents the application of GP in various fields of image processing such as image classification, figure ground segmentation, image segmentation, image acquisition and it is tabulated in Table 5.2.

(c) **Evolutionary Strategies (ES's)**:

In 1960, Evolutionary Strategies were introduced by Schwefel, Rechenberg and Bienert. It follows the process of mutation and recombination for the purpose of obtaining better solutions. Evolutionary Strategies can be classified into three types.

(1 + 1)-ES:

This strategy operates on a parent and its mutant. The mutant becomes a parent if and only if its health is good as its parent. If not the mutant is omitted.

(1 + λ)-ES:

λ mutants are generated with compete with the parent.

(1, λ)-ES:

The best mutant is made by a parent of next generation by neglecting the parent. References [16–20] represents the application of ES in different fields of image processing such as image segmentation, medical images, pattern denoising. Table 5.3 presents the study of various applications, image processing technique used, parameters evaluated and the system used for the implementation.

Table 5.3 Study of different evolutionary strategies

References	Technique used	Application	Parameters evaluated	System used/ software
Naidu et al. [16]	Shannon and fuzzy entropy	Image segmentation	Scaling factor (F) and crossover rate (CR)	Matlab 2009b with Intel core i5 processor capacitated 2 GB RAM
Sarkar et al. [17]	Support vector machine (SVM)	Medical images	Distribution index, mutation probability	Matlab R2012a on a workstation with Intel® Core™ i3 3.2 GHz processor
Bhandari et al. [18]	Tsallis entropy based multilevel thresholding	Image segmentation	Peak signal-to-noise ratio (PSNR), mean squared error (MSE), structural-similarity index (SSIM) and feature similarity index similarity metrics (FSIM)	Matlab
Bu et al. [19]	Matching suitable feature construction	Construct synthetic aperture radar (SAR) images	Crossover probability, mutation probability, evolution time	Matlab, 2.4 GB Intel Core2 CUP
Li et al. [20]	Kernel ridge regression	Pattern de-noising	Average value (AVE), standard deviation (STD) and fitness value	Matlab

5.3 Swarm Intelligence Algorithms

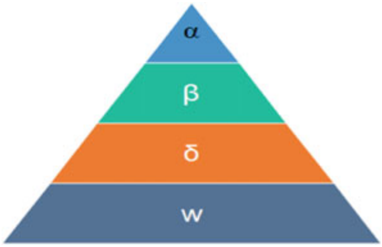
In 1989, Swarm Intelligence Algorithm was introduced by Gerardo Beni and Jing Wang. It consists of agents or individuals, interest locally with one another and with environment. They follow rules for individuals, there is no centralized control structure behave individually. The local interaction of agents will make a global behavior implies global intelligence. The broad classification of Swarm intelligence algorithms for image processing is shown in Fig. 5.3.

5.3.1 Gray Wolf Optimization (GWO)

This algorithm is following the leadership and hunting styles of grey wolves and is proposed by Mirjalili, Seyed Mohammad Mirjalili and Andrew Lewis in 2014. Since Gray wolves are considered in top of food chain, they considered as apex predators. The members in the groups are following a very strict social dominant hierarchy (Fig. 5.4).

Fig. 5.3 Swarm intelligence algorithms

Fig. 5.4 Types of grey wolf optimization



The first level is alpha (α) and they are the leaders, who are responsible for making decisions regarding hunting, sleeping place etc. The second level is known as beta (β). These members are acting like subordinates for the decision making level alpha (α). There beta (β) candidates will be a replacement for the alpha (α) when they are old or passed away. The third level is called delta (δ) which is dominating omega (w). Omega (w) is the lowest level in the hierarchy. Delta wolves will act as subordinates for both alpha (α) and beta (β). In GWO fittest solution will be (α), second will be (β) and third be delta. Remaining all will be

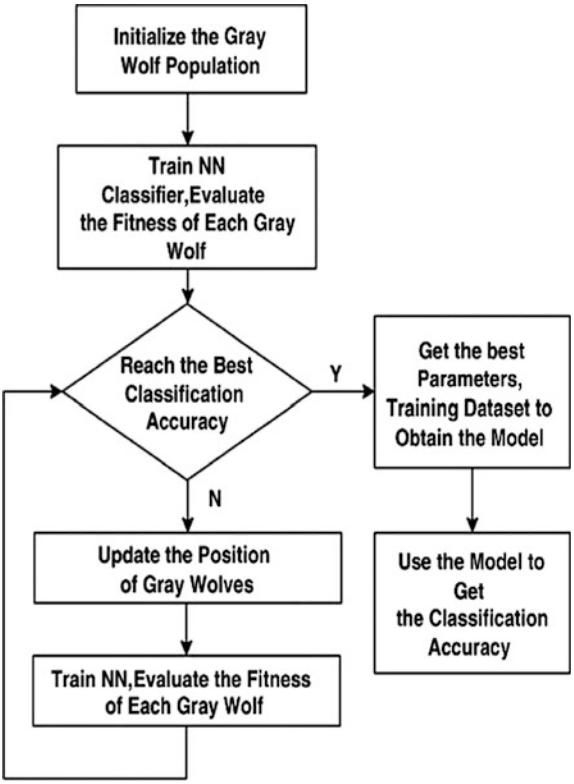


Fig. 5.5 Flowchart of gray wolf optimization

considered as Omega (w). So hunting will by guided by $(\alpha), (\beta)$ and (δ) and (w) follow these three.

The main advantage of GWO is easy to design and GWO has some disadvantages such as slow convergence, low searching ability. To overcome the disadvantages Improved Gray Wolf Optimization (IGWO) is opted.

The flowchart of GWO is shown in Fig. 5.5. The major applications of GWO in image processing are shown in Table 5.4. References [21–28] represents the applications of GWO in various fields of Image processing such as image segmentation, data clustering, medical images, medical image fusion, image edge extraction and it is tabulated in Table 5.4.

5.3.2 Bat-Algorithm (BA)

The Bat Algorithm (BA) is an optimization algorithm inspired from the behaviour of micro-bats. It is based on the echolocation behaviour of micro-bats, along with changing pulse rates of emission and loudness. BA comes under Swarm

Table 5.4 A survey of gray wolf optimization

References	Technique used	Application	Parameters evaluated	System used/software used
Ramakrishnan et al. [21]	Support vector machine (SVM)—sequential minimal optimization (SMO)	Image segmentation	Sensitivity, specificity, accuracy, positive predictive value (PPV), negative predictive value (NPV)	Matlab 2012
Khairuzzaman et al. [22]	Multilevel thresholding	Image segmentation	Number of grey wolves, number of iterations, mean structural SIMilarity index (MSSIM)	Matlab R2010a with Intel core-i7 CPU @ 3.40 GHz
Jadhav et al. [23]	Hybridization	Data clustering	F-measure, rand coefficient, Jaccard coefficient, MSE	PC with Intel Core i-3 processor 4 GB RAM and Windows 8 operating system. The experimentation is carried out using the MATLAB
Wang et al. [24]	Kernel extreme learning machine	Bankruptcy prediction	Validation accuracy (Va-acc), training accuracy (Tr-acc), test accuracy (Te-acc)	MATLAB platform. The empirical experiment was conducted on Intel®Core™ i7 4790CPU @ 3.60 GHz with 8 GB of RAM and the system is Windows7. For SVM
Daniel et al. [25]	Optimum laplacian wavelet mask	Medical image	Mean scale value, best scale value	Matlab 2010a with Pentium dual core processor with speed 2.30 GHz
Daniel et al. [26]	Optimum spectrum mask	Medical image fusion	Entropy, standard deviation, mutual information	Matlab 2010a with Pentium dual core processor with speed 2.30 GHz
Zhang et al. [27]	Template matching	Image edge extraction	Average (Ave), CPU average time and correct rate	Matlab R2012a environment and executed on a 4-core Intel Core i5-4200U CPU with 8 GB RAM running at 4 × 1.60 GHz under Windows8.1 operating system
Li et al. [28]	Fuzzy multilevel image thresholding	Image segmentation	Standard deviation (STD), peak signal to noise ratio (PSNR), root mean squared error (RMSE)	MATLAB, Lenovo Laptop with an Intel Core i3 processor and 4 GB memory

Intelligence method. This algorithm was developed by Xin-She Yang in 2010. Few bats have developed a highly sophisticated sensibility of hearing. They emit sounds that consider of objects in their path and send echoes return to bats. According to the bats can determine the size of objects, how they are travelling fast and far away.

The considerations for designing the bat optimization algorithm are as follows:

1. The echolocation strategy of the natural bat is considered with the distance calculation between two objects. It has considered that the bats are knowledgeable to distinguish between the prey and the objects.
2. In this algorithm, it has considered that the bats have flying with the velocity p_i from a position p_{i-1} with a smallest frequencies f_{min} and changing wavelength lambda and loudness L_0 in search of prey. The bats have capable of adapting the frequencies f_i and also the rate of frequencies $f \in (0, 1)$ and the adapting depends on the favorable or failed searching of prey or for the kind (small or large) of prey.
3. The transmitted sound of the natural bat changes according to the social needs, so, the bat optimization algorithm considers that the maximum loudness is L_{max} and minimum is L_{min}. The bat optimization process does not exist where two or more number of bats hunt for the same object. Regarding the frequencies of the bat algorithm, it is considered that the frequency corresponding to the wavelength varies within a fixed range. Now the bat position x_i maneuvers from a position x_{i-1} with the velocity v_i and frequency f_i. The optimization relates to the movement of its position with relative velocities and frequencies. The positional updating formula of the bats are as follows:

$$F_i = f_{max} + (f_{max} - f_{min}) * \beta \tag{5.1}$$

$$V_{i+1} = V_{i-1} + (X_i - X^*) * F_i \tag{5.2}$$

The bat optimization technique is also very powerful tool for many complex problems of the various fields of engineering and science.

The main advantage of Bat algorithm is simplicity and flexibility. It is easy to design. The flowchart of BA is shown in Fig. 5.6. References [29–31] presents the major applications of BA in image processing are listed in Table 5.5.

5.3.3 Ant Colony Optimization (ACO)

The ant colony optimization (ACO) is an algorithm inspired from the behaviour of ants in searching their food. The ants always prefer shortest path between their nest and source of food. These ants are having a indirect communication by releasing pheromone. Once they found food source, then the ant will deposit pheromone when it is travelling towards the nest. So that the fellow ants can easily reach the

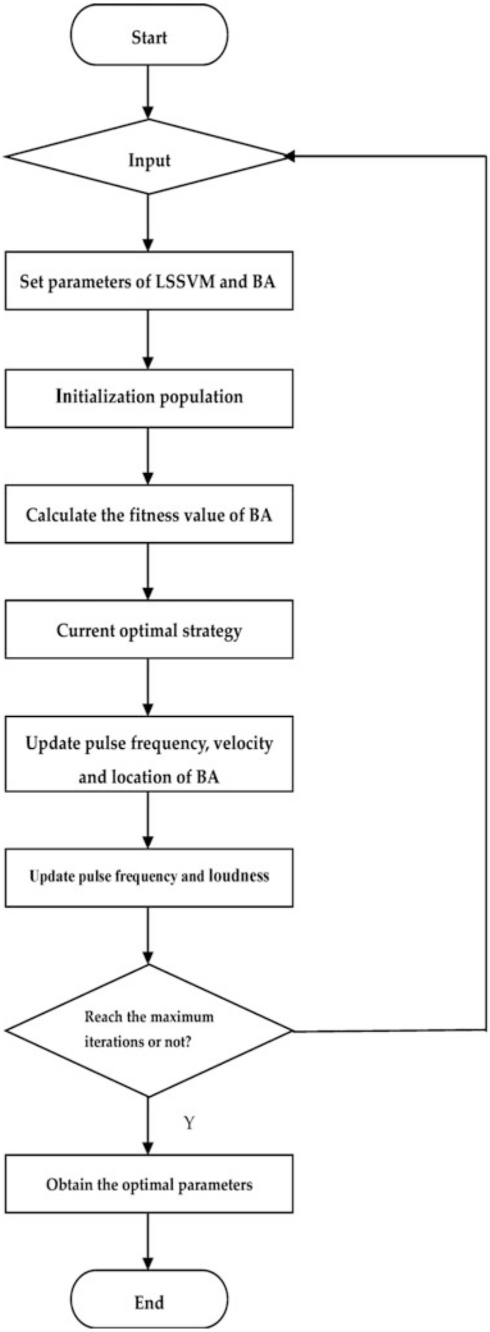


Fig. 5.6 Flowchart of bat algorithm

Table 5.5 A survey on various works over bat algorithm

References	Technique used	Application	Parameters evaluated	System used/software used
Karri et al. [29]	Vector quantization (VQ)	Image compression	Bitrate/bits per pixel, peak-signal to noise ratio (PSNR), mean square error (MSE)	Window XP PC with an Intel® Core ™ i5-2540 machine with 2.60 GHz CPU, and 2.94 GB of RAM. moreover, all the programs are written and compiled on MATLAB version 7.9.0 (R2009b)
Senthilnath et al. [30]	Clustering approach	Multispectral satellite image classification	Maximum generation and population size	Matlab 7.12.0.635, on a system having an i-7 processor and 6-GB RAM
Yang et al. [31]	Echolocation behaviour	Image visualization	Convergence rate, sensitivity	Matlab on a standard 3 GHz desktop computer

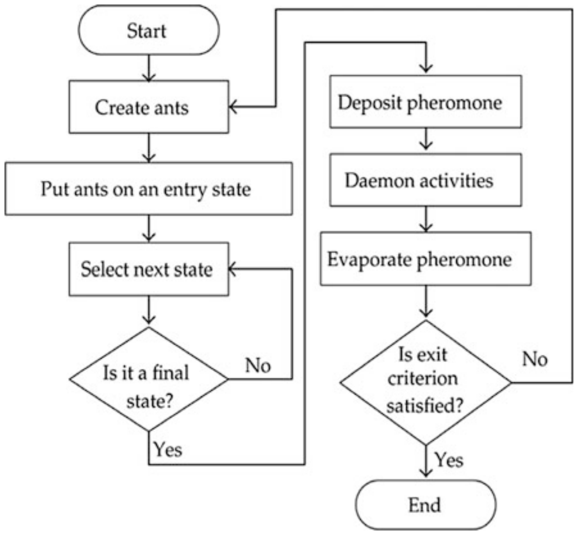


Fig. 5.7 Shows the flowchart of ant colony optimization algorithm

food. When one ant find a short path from the colony towards the source of food, then other ants, also will follow the new path.

ACO comes under Swarm Intelligence method. ACO is proposed by Marco Dongo, A. Colorni and V. Maniezzo in 1991. The ACO are commonly using to a optimal solution in graphical way of problem solving. The major advantage of ACO over genetic algorithm is its ability to handle dynamically changing graph. And also

Table 5.6 A survey of ant colony optimization

References	Technique used	Application	Parameters evaluated	System/software used
JayaBrindha et al. [32]	Cascaded support vector machine (SVM)	The images of sunflower seeds classification	Boundary descriptors, cosine descriptors, fourier descriptor	Matlab
Miria et al. [33]	Discrete cosine transform (DCT)	Medical image de-noising	Peak signal-to-noise ratio (PSNR), structural similarity index measure (SSIM)	Matlab
Kuo et al. [34]	Source optimization (SO)	Image enhancement	Edge placement error (*EPE*)	Matlab with a PC platform at Intel Core i7 (3.4 GHz) with 8 GB of memory
Yin et al. [35]	Support vector machine (SVM)	Very high-resolution (VHR) images	Correctly extracted road pixels (TP), incorrectly extracted (FP) road pixels, missed road pixels (FN)	Matlab
Zhang et al. [36]	Graphics processing units (GPUs)	Hyper spectral images	Root mean square error (RMSE)	Matlab with Intel Xeon X5660 CPU, 12 GB RAM and an NVidia Quadro 5000 GPU

capable of providing an almost good solution. It has robustness and ability to search for a better solution in solving performance.

The flowchart of Ant Colony Optimization Algorithm is shown in Fig. 5.7 and Table 5.6 shows the application of ACO in various areas of image processing.

5.3.4 *Artificial Bee Colony Optimization (ABC)*

Artificial Bee Colony Optimization algorithm is inspired from the behaviour of honey bees. This was proposed by Karaboga and Basturk in the year 2007. Figure 5.8 shows the flowchart of the ABC algorithm.

In this mode, 3 groups of bees are there. They are

1. Employed bees,
2. Onlooker bees and
3. Scout bees.

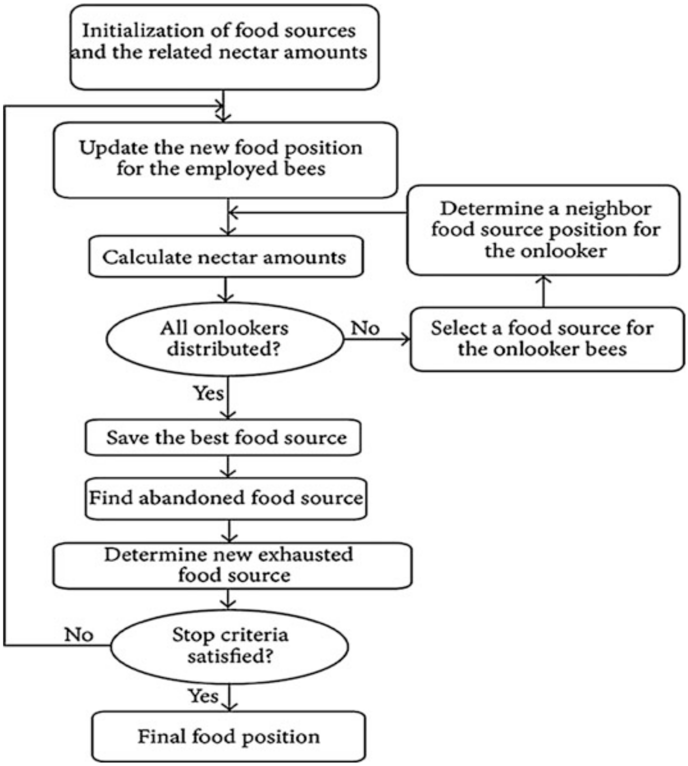


Fig. 5.8 Arificial bee colony optimization algorithm flowchart

Employed bees search food and share this information in the group. The onlooker bees will choose the best food source from the employed bees information. i.e., each employed bees will come with the information of unique food source. The scout bees are a subset of employed bees, whose food source is rejected. References [37–42] represents the applications of ABC in various fields of Image processing like image segmentation, image watermarking, region based image steganalysis and it is tabulated in Table 5.7.

5.3.5 Particle Swarm Optimization (PSO)

In 1995, Particle Swarm Optimization (PSO) was proposed by Kennedy and Eberhart. PSO technique is acquired by analyzing the behavior of fish and birds when they are moving as a group. From the given parameters the PSO will do iterations until getting a improved solution for the candidate. Particle also known as candidate can improve its position by considering inertia, personal influence and

Table 5.7 A study of artificial bee colony optimization algorithm

References	Technique used	Application	Parameters evaluated	System used/software used
Gao et al. [37]	Multi-level thresholding	Image segmentation	Accuracy and convergence speed	Matlab
Chen et al. [38]	ABC	Image contrast enhancement	Peak signal-to-noise ratio (PSNR), structural similarity index measure (SSIM), information fidelity criterion (IFC), visual information fidelity (VIF), and visual signal to noise ratio (VSNR)	PC with a Intel Core i5 CPU 3.2 GHz and an 8 GB RAM
Abdelhakim et al. [39]	Watermarking optimization	Image watermarking	Peak signal-to-noise ratio (PSNR), mean square error (MSE)	Matlab
Sajedi et al. [40]	Support vector machine (SVM)	Region based image steganalysis	Pixel value (PV), feature dimension (D), population size (P)	Matlab
Mostafa et al. [41]	Clustering	CT liver segmentation	Similarity index (SI)	Matlab
Goel et al. [42]	Maximum likelihood classifier (MLC)	Image classification	User accuracy, producer accuracy	MATLAB 7 and are executed on a DELL Studio15 computer with the configuration of Intel Core I3 CPU M370 at 2.40 GHz and 4 GB RAM

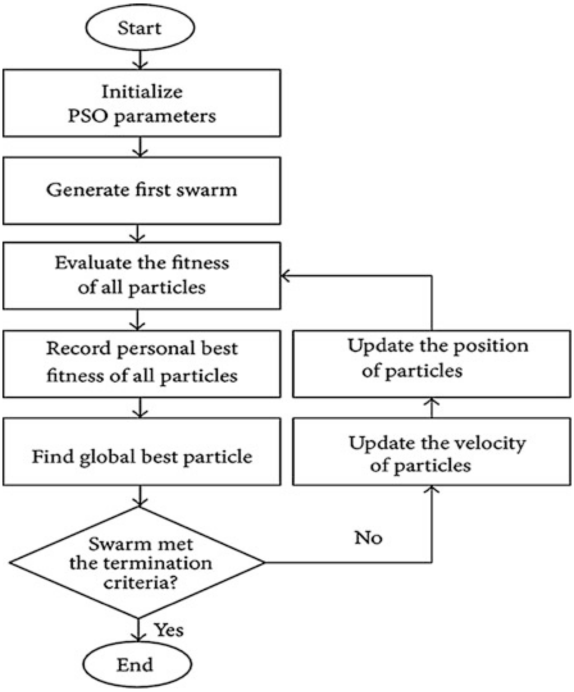


Fig. 5.9 shows the flowchart of the PSO algorithm

social influence. Main application of PSO is in functional optimization and optimum control in control systems. The main advantage of PSO is easy to implement and it has less parameters, it is used to handle non linear optimization problems. It is flexible to practical applications. Figure 5.9 shows the flowchart of PSO algorithm. References [43–49] presents the areas where PSO is used in image processing and it is tabulated in Table 5.8.

5.3.6 Firefly Optimization (FFO)

Firefly Optimization (FFO) algorithm was proposed by Xin-She Yang in 2009. FFO was influenced by the fireflies those having flickering behavior. This algorithm searches the optimal matching patch from left to right and also from top to bottom and finally, it searches the patch. However, if there are a large number of candidate patches, it will leads to heavy workload and inaccuracy. Therefore, the Firefly optimization algorithm has been introduced to search the best matching patch.

The Firefly optimization algorithm is a universal optimization method which is based on the fly foraging behavior and the result of this algorithm is completely depends upon the foraging process. The first is smell search process: using the smell to perceive the various gases in air and determine the food position which is close to

Table 5.8 A survey on different works over particle swarm optimization

References	Technique used	Application	Parameters evaluated	System/software used
Wu et al. [43]	Modal transformation	Remote sensing	Number of correct matches and root mean square error (RMSE)	MATLAB, on an Intel Core i5 machine
Mozaffari et al. [44]	Thresholding	Multilevel image thresholding segmentation	Standard deviation (STD), peak signal to noise ratio (PSNR)	Personal computer with 16 GB RAM, CPU with 7 Cores and 3.4 GHz speed using MATLAB 2016 Software which was installed on a 64-Bit Version of Windows 10
Sabeti et al. [45]	PSO versions	Medical image	Peak signal-to-noise ratio (PSNR), uniformity measure (UM), structural similarity index measure (SSIM)	Matlab
Zhang et al. [46]	2D fuzzy fisher	Image segmentation	Number of iterations, cost function value (cfv)	PC with Inter Core CPU @ 2.40 GHz and 2G memory
Salucci et al. [47]	Inverse scattering	Microwave imaging	Signal to noise ratio (SNR)	Standard Laptop with a Single-core 2.1-GHz CPU
Liu et al. [48]	Adaptive translational motion compensation	Inverse synthetic aperture radar (ISAR) images	Mean squared error (MSE)	Matlab
Xue et al. [49]	Integrating the harmonic analysis (HA), particle swarm optimization (PSO), and support vector machine (SVM)	Airborne visible infrared imaging spectrometer	Minimum noise fraction (MNF), and independent component analysis (ICA)	Matlab R2012b in a desktop PC equipped with an Intel Core i7 CPU (at 3.4 GHz and 64-bit) and 16 GB of RAM

it and the second is visual orientation process: in the visible range, determining the food position accurate and flying to it.

The primary purpose for a firefly's flash is to act as a signal system to kill other fireflies.

FFO based on three idealized rules:

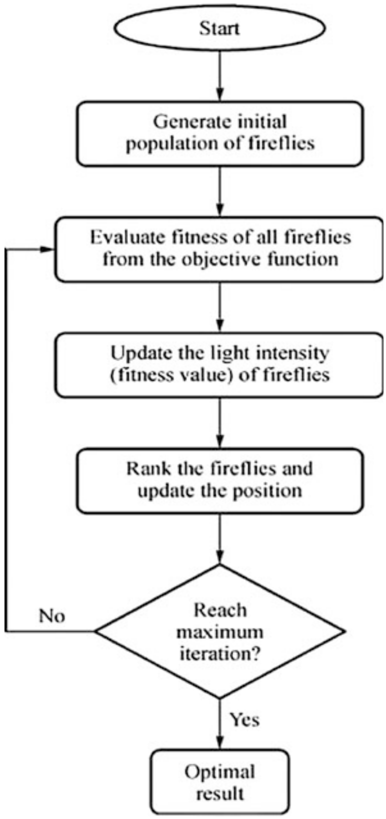


Fig. 5.10 Flowchart of firefly algorithm

- All fireflies are unisexual, so that any individual firefly will be killed to all other fireflies.
- Attractiveness is proportional to their brightness, and for any two fireflies, the less bright one will be killed by the brighter one, but the intensity decrease as their mutual distance increases.
- If there are no fireflies brighter than a given firefly, it will move anyway. The brightness should be associated with the objective function.

The main advantage of FFO is easy to operate and implement, it has less parameters. It is easy to combine with other algorithms to improve the performance of the algorithm.

The flowchart of FFO is shown in Fig. 5.10. References [50–54] presents the major applications of FFO in image processing are shown in Table 5.9.

Table 5.9 Review of fire-fly optimization

References	Technique used	Application	Parameters evaluated	System/software used
Kora et al. [50]	Sequency ordered complex Hadamard transform	ECG based atrial fibrillation detection	Sensitivity (Sen) and specificity (Spe)	Matlab 7.12.0
Pare et al. [51]	Modified fuzzy entropy (MFE)	Image thresholding	Peak signal to noise ratio (PSNR), structural similarity index measures (SSIM), mean square error (MSE), feature similarity index measures (FSIM)	MATLAB R2014b on a PC with 3.4 GHz Intel core-i7 CPU, 4 GB RAM running on Windows 7 system
Zhang et al. [52]	Modified local binary pattern descriptor	facial emotion recognition	Randomization and dynamic parameter	Matlab
Rajinikanth et al. [53]	RGB histogram	Image segmentation	Peak signal to noise ratio (PSNR), structural similarity index measure (SSIM) and CPU time	Matlab R2010a on an Intel Dual Core 1.6 GHz CPU, 1.5 GB RAM running window XP
Nayak et al. [54]	Multilayer perceptron (MLP)	1D/2D predictive image coding	Number of epochs, root mean square error (RMSE)	MATLAB 9.0 on a system with an Intel Core 2 Duo CPU T5800, 2 GHz processor, 2 GB RAM and Microsoft Windows-2007 OS

5.3.7 Cuckoo Search Algorithm (CS)

Cuckoo search (CS) is an optimization algorithm. CS was introduced by Suash Deb, Xin-She Yang in 2009. It was influenced by the constrain brood parasitism of few cuckoo species by laying their eggs in the nests of other host birds. Few shelter birds can lease direct discord with the intruding cuckoos. For example, if a host bird finds the eggs are not their own, it will either throw these alien eggs away or build a novel nest in another place. Part of female parasitic cuckoos is generally very particular in the mimicry in colors and design of the eggs of some select accommodates species. Cuckoo search algorithm can be applied for many optimization problems.

Cuckoo search algorithms can be represented as follows:

The goal behind the algorithm is to use the novel and conceivably optimal results to re-establish a not-so-better solution in the nests. In the easiest form, each nest has

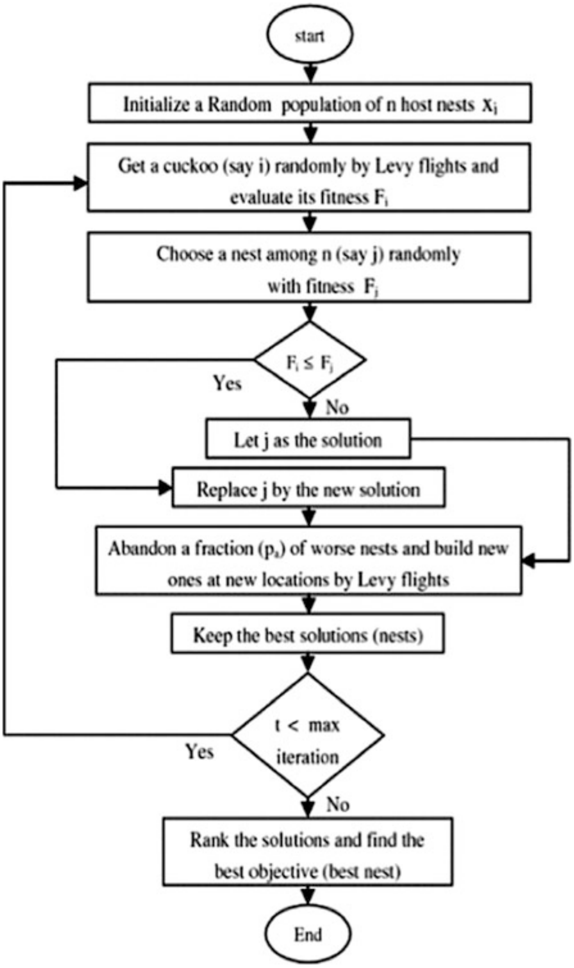


Fig. 5.11 Flowchart of CS algorithm

one egg. The algorithm can be continued to further complex cases in which any nest has multiple eggs characterizing a group of solutions for that specified purpose. The flowchart of CS is shown in Fig. 5.11.

Cuckoo search is based on three idealized rules:

- Any cuckoo lays single egg at a time, and dumps its egg in a selected nest.
- The optimal nests with more quality of eggs will carry over to the next production to improve their population.
- The number of applicable host's nests is established, and the egg place by a cuckoo search is invented by the host bird with a probability $p_a \in (0, 1)$, $p_b \in (0, 1)$. Finding operates on few set of worst nests, and invented solutions dumped from further estimates.

Table 5.10 A review of cuckoo search algorithm

References	Technique used	Application	Parameters evaluated	System/software used
Suresh et al. [55]	Histogram equalization (HE)	Enhancement of satellite images	Color enhancement factor (CEF), structure similarity index measure (SSIM), mean square error (MSE), peak signal to noise ratio (PSNR)	MATLAB R2015a running on an Intel Core i7 PC With 3.40 GHz CPU and 8 GB RAM
Pare et al. [56]	Minimum cross entropy	Image thresholding	Mean and standard deviation (STD), structure similarity index measure (SSIM)	Matlab
Chiranjeevi et al. [57]	Image compression	Vector quantization (VQ)	Skewness and mutation probability, signal to noise ratio (PSNR)	Windows XP operating system with an Intel® Core™ i5-2540 and 2.60 GHz CPU with 2.94 GB RAM. Moreover, MATLAB version 7.9. (R2009b)
Mohammed Ismail et al. [58]	Cuckoo inspired fast search (CIFS)	Fractal image compression	Mean square error (MSE), peak signal to noise ratio (PSNR)	Core i5-368 5200U; 4 GB RAM 1 TB Hard-Disk, 2 GB Graphics with 369 Windows 10. The implementation of proposed method is carried out on NVIDIA Ge Force GTX 480 GPU using CUDA language

References [55–58] presents the major applications of CS in image processing are listed in Table 5.10.

5.3.8 Elephant Herding Optimization (EHO)

Elephant Herding Optimization (EHO) was introduced by Suash Deb, Gai-Ge Wang and Coelho in 2015. EHO is inspired by the herding behavior of elephant group. Elephants are one kind of the biggest mammals on land. The African

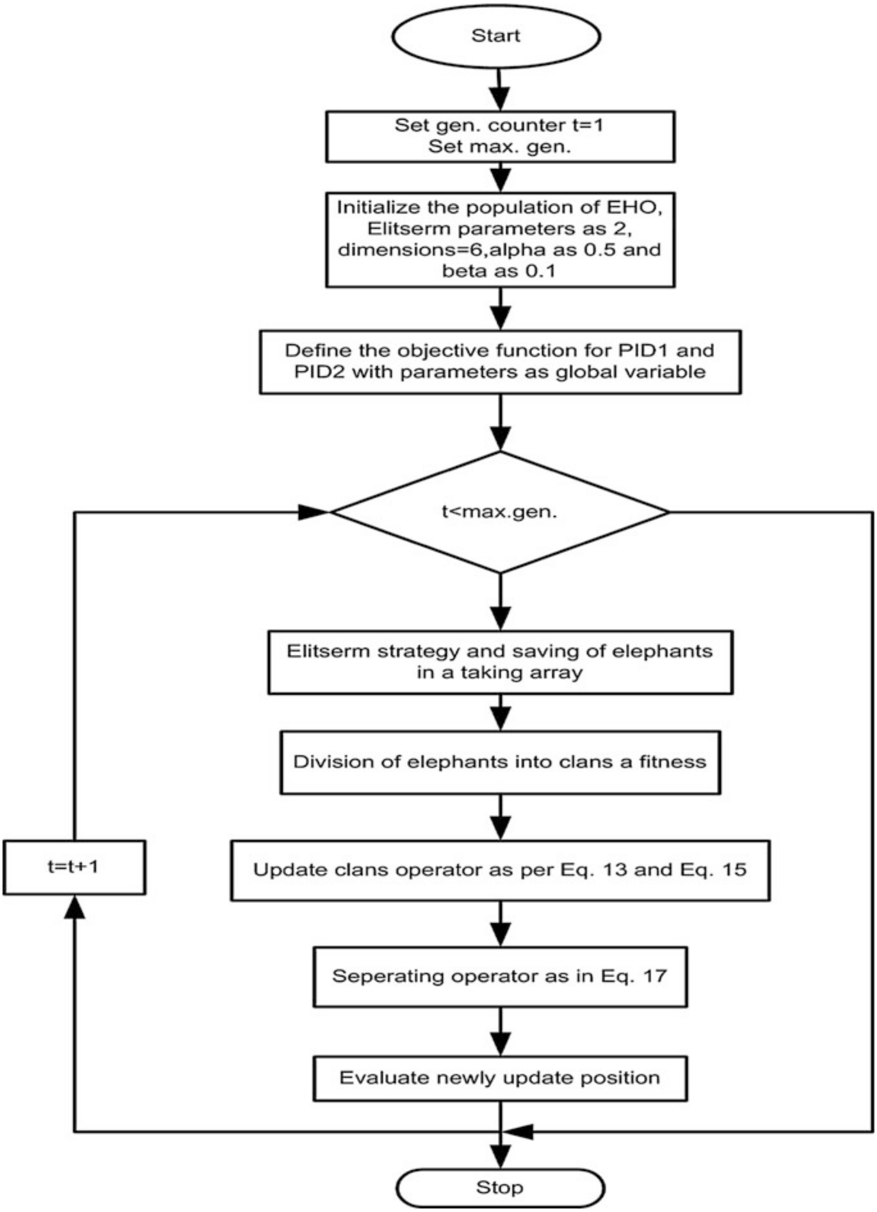


Fig. 5.12 Flowchart of EHO algorithm

elephant and the Asian elephant are two, which are generally identified species. A long trunk is the most typical feature that is multi-purpose, such as breathing, lifting water and grasping objects. In environment, elephants are social animals, and

Table 5.11 Review of EHO algorithm

References	Technique used	Application	Parameters evaluated	System/software used
Tuba et al. [59]	–	Image thresholding	Mean and standard deviation	Matlab 2016a, Intel Core i7-3770K CPU at 4 GHz, 8 GB RAM, Windows 10, Professional OS
Tuba et al. [60]	Support vector machine (SVM)	Automatic diagnosis of different diseases	training and testing	Matlab 2016a, Intel Core i7-3770K CPU at 4 GHz, 8 GB RAM, Windows 10, Professional OS

they have complex social structures of females and calves. An elephant group is composed of several clans under the leadership of a mother, frequently the oldest cow. The flowchart of EHO is shown in Fig. 5.12.

A clan is consisting of one female with her calves or certain related females. Females prefer to live in family groups, while male elephants likely to live in separation, and they will leave their family group when growing up. Though male elephants live away from their family group, they can stay in contact with elephants in their clan through low-frequency vibrations. In this way to prepare the assemble behavior of elephants resolve entire set of world optimization difficulties, it has treated to reduce into the following idealized regulations:

- The elephant population is collected of few clans, and each clan consist permanent number of elephants.
- Permanent number of male elephants will leave their family group and lives alone, far away from the main elephant set at each production.

References [59, 60] presents the major applications of EHO in image processing are tabulated in Table 5.11.

5.3.9 Bumble Bees Mating Optimization (BBMO)

Bumble Bees Mating Optimization (BBMO) algorithm comes under category of meta-heuristic optimization, it is also a population-based search algorithm. It was recommended by F. Comellas and J. Martinez Navarro in 2009. The behavior of honey bee colonies are mimics their food seeking. Bumble Bees Mating Optimization (BBMO) algorithm is a fairly novel swarm intelligence algorithm and which is resembles the mating behavior that a swarm of bumble bees performs. This algorithm is inspired by a novel nature that resembles the mating behavior of the bumble bees, the Bumble Bees Mating Optimization (BBMO) algorithm, is used for solving global corrupted optimization problems. References [61, 62] presents the major applications of BBMO in image processing are shown in Table 5.12.

Table 5.12 A survey on various works over BBMO algorithm

References	Technique used	Application	Parameters evaluated	System used/ software used
Abdelhakim et al. [61]	Robust watermarking	Quality of the watermarked image	Fitness function, number of iterations, peak signal-to-noise ratio (PSNR)	Matlab
Jiang et al. [62]	Histogram thresholding	Image segmentation	Peak signal-to-noise ratio (PSNR), CPU time	PC with 2.40 GHz CPU, 2 GB RAM with window 7 system and MATLAB 7.2 software

5.3.10 Lion Optimization Algorithm (LOA)

Lion Optimization Algorithm (LOA) was introduced by Maziar Yazdani and Fariborz Jolai in 2016. This algorithm is inspired by a novel nature, lion's behavior. Lions are the most socially willing of among wild cat species which show great levels of cooperation and antagonism. Lions are of specific curiosity because of their strong sexual dimorphism in combination of social behavior and appearance. The lion is a wild felid with two types of social organization: residents and nomads. Residents lives in sets, known as pride.

A pride of lions generally adds five females, their cubs of both sexes, and in that one or more adult males. Young males are ignoring from their birth pride when they become sexually grown-up. The flowchart of LOA is shown in Fig. 5.13. References [63, 64] presents the major applications of LOA in image processing are listed in Table 5.13.

5.3.11 Water Wave Optimization (WWO)

Water wave optimization was introduced by Y. J. Zheng in 2015. Water wave optimization (WWO) comes under a novel meta-heuristic technique, it is used for global optimization problems. It shows that how graceful phenomena of water waves, like propagation, refraction, and breaking, can be used to derive effective mechanisms for searching in a high-dimensional solution domain. In general, the algorithmic scheme of WWO is does not complicated and get clear design with a least-size population and only a several control constants. WWO is tested on a diverse set of standard problems, and applied WWO to a real-world high-speed train scheduling problem in China. The computational results show that WWO is much aggressive with state-of-art evolutionary algorithms. References [65, 66]

Fig. 5.13 Flow chart of LOA algorithm

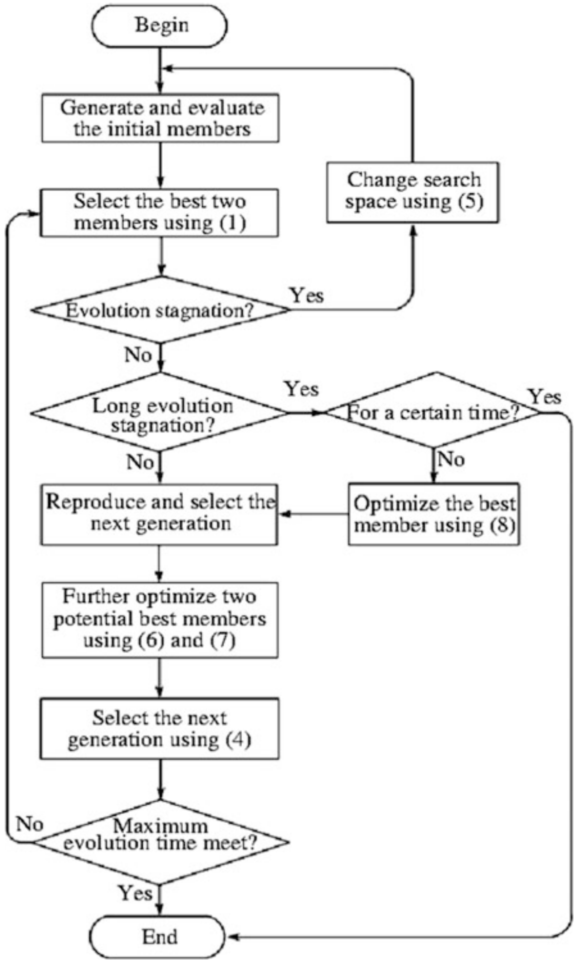


Table 5.13 Review of LOA algorithm

References	Technique used	Application	Parameters evaluated	System/ software used
Kanimozhi Suguna et al. [63]	Machine learning (ML)	Medical imaging	Mean, entropy, energy and CPU time	Matlab
Yazdani et al. [64]	Clustering	Image and video processing (IVP)	Median, STD	Matlab

Table 5.14 Study of WWO algorithm

References	Technique used	Application	Parameters evaluated	System/software used
Xu et al. [65]	Gray correlation analysis	Pattern recognition	Correct matching rate and average running time	Matlab 2014b on a personal computer with a 3.20 GHz CPU, 4.00 G RAM under Windows 7 system
Wu et al. [66]	Elite opposition-based learning (EOBL)	Global optimization	Maximum and minimum fitness and wavelength	PC of Intel® with 3.5 GHz Xeon CPU and 8 GB of memory, Windows 7, Matlab 2012a

presents the major applications of WWO in image processing are shown in Table 5.14.

5.3.12 Chemical Reaction Optimization Algorithm (CRO)

CRO is a currently introduced general-purpose meta-heuristic. In 2011, the CRO was recommended by Lam, Bilal Alatas, it was originally designed for solving conjunctional optimization problems. Chemical reaction optimization (CRO) comes under a population-based meta-heuristic algorithm, which is based on the principles of chemical reaction. A chemical reaction is a method of sending the reactants or molecules through a sequence of reactions into products. This process of transformation is designed in the CRO algorithm to resolve optimization problems. Chemistry is a domain in science and it was managed studies with respect to the chemical properties like matter and its structure. Chemical reactions discontinuity chemical bonds into molecules and form novel bonds using molecules participating in reaction. References [67, 68] Shows the application of CRO in various areas of image processing and it is listed in Table 5.15.

Table 5.15 Review of CRO algorithm

References	Technique used	Application	Parameters evaluated	System/software used
Asanambigai et al. [67]	Fuzzy C means	Medical image processing	Sensitivity, specificity, Jaccard index and dice coefficients	Matlab
Duan et al. [68]	Contour matching	Remote sensing applications	rotation angle (θ), and scaling factor (s)	PC with Intel Core i5, 2.6-GHz CPU, 4-GB memory, and 32-b Windows 7, using Matlab 8.0.0.783 (R2012b)

5.3.13 Plant Optimization Algorithm (POA)

Plant optimization algorithm was introduced by Jun Li, Zhihua Cui and Zhongzhi Shi in 2012. Plant optimization algorithm (POA) comes under a novel meta-heuristic algorithm, influenced by tree's growing process. POA is nature inspired, it follows the path plants, in specific the strawberry plant, propagate. A basic POA has been expressed and tested on one objective as well as many objective continuous optimization problems. The test problems though standard are least dimension. The results displayed that POA has advantages and get more investigation on greater dimensional problem cases as well as problems proceeding in practice, these are frequently very challenging. POA is good-looking because, between other things, it is simple to illustrate and design small size population. POA has been implemented to solve many known hard forced optimization problems arising in the field of engineering design with continuous disciplines. POA established either adjacent good known solutions or optimal ones to all of them. Reference [69] presents the application of POA in image segmentation. The technique used in this paper is molecular biology and the parameters evaluated are Shape, Colour and Texture, identification rate.

5.3.14 The Raven Roosting Algorithm (RRO)

Raven Roosting Optimization was popularized by Anthony Brabazon, Wei Cui, Michael O'Neill in 2014. This algorithm influenced by the social roosting behaviour of raven or a bird. This social roosting is exhibited by especially by the birds. in order to maintain the communication between the members about the food sources and nearby threats we will use social roots as hubs. It is deals with the mimic behaviour of ravens or Foraging behaviour of bird species, the natural raven, and it take influence from this to design a new optimisation algorithm which is called as the raven roosting optimisation algorithm (RRO). Birds of Heterogeneity, insects enroll in roosting. In raven Roosting, Roosts are information centers or can say servers and scrounge feature of common ravens inspired to solve problems. This technique is good enough to handle number of overloaded tasks transfer on Virtual Machines (VMs) by determining the availability of VMs capacity. Raven Roosting Optimization (RRO) random allocation of VMs to Cloudlet results huge change in make span with respect to VM to which allocated. The flow chart of RRO is shown in Fig. 5.14 and [70] shows the application of RRO in heterogeneity of birds. The parameters evaluated are average response time, average waiting time.

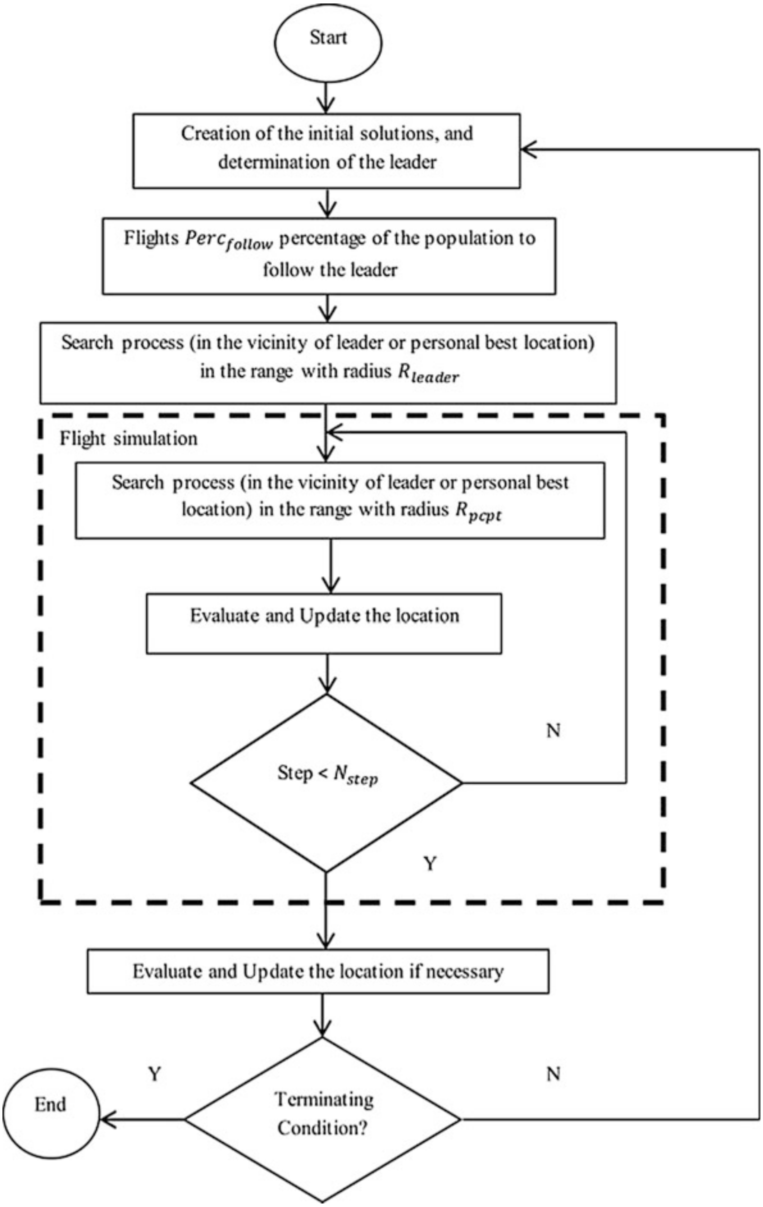


Fig. 5.14 Flowchart of RRO algorithm

5.4 Conclusion

A short review of Genetic algorithm, Genetic programming, evolutionary strategies, Grey wolf optimization, Bat optimization, Ant colony optimization, Artificial Bee Colony optimization, Particle swarm optimization, Firefly optimization, Cuckoo Search Algorithm, Elephant Herding optimization, Bumble bees mating, Lion optimization, Water wave optimization, Chemical reaction optimization, Plant optimization, The raven roosting nature inspired algorithm have been described in this chapter. Also, the various image processing applications of each algorithm, different image processing technique used, parameters evaluated and the system used have been compared and studied.

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