Archives of Computational Methods in Engineering (2019) 26:1607–1638
https://doi.org/10.1007/s11831-018-9289-9

ORIGINAL PAPER

A Survey on Nature-Inspired Optimization Algorithms and Their Application in Image Enhancement Domain

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Received: 16 March 2018 / Accepted: 1 September 2018 / Published online: 10 September 2018

Abstract

In the field of image processing, there are several problems where the efficient search has to be performed in complex search domain to find an optimal solution. Image enhancement which improves the quality of an image for visual analysis and/or machine understanding is one of these problems. There is no unique image enhancement technique and it's measurement criterion which satisfies all the necessity and quantitatively judge the quality of a given image respectively. Thus sometimes proper image enhancement problem becomes hard and takes large computational time. In order to overcome that problem, researchers formulated the image enhancement as optimization problems and solved using Nature-Inspired Optimization Algorithms (NIOAs) which starts a new era in image enhancement field. This study presents an up-to-date review over the application of NIOAs in image enhancement domain. The key issues which are involved in the formulation of NIOAs based image enhancement models are also discussed here.

1 Introduction

Image enhancement is for processing an image such that it improves the interpretability or perception of information in images for human viewers. It is mainly application oriented and the enhanced image may visually good than original one [1]. The word application oriented signifies that the enhancement methods useful for enhancing a pathological image are may not be suitable for enhancing X-ray images or Magnetic Resonance images (MRI) or satellite images. Reduction of noise is also a form of image enhancement. In many cases, it has been found that captured image is very dark due to various reasons. In such cases, image enhancement technique may need to increase contrast or intensity of the image. All the enhancement method increases the dynamic range of the chosen features such that they can be detected easily.

Image enhancement approaches fall into two broad categories, spatial domain methods and frequency domain methods [1]. The term spatial domain refers to the image plane itself, and approaches in this category are based on direct manipulation of pixels in an image. Whereas, frequency domain processing techniques are based on the transformed domains such as Fourier [2], Hartley [2], cosine [2], Hadamard [2], Wavelet [3], Curvelet [4] transforms etc. for modifying the image [1]. In spatial domain, the operation can have three different forms, namely point processing; histogram based processing and masks processing technique. Histogram-based processing technique can also be called point processing technique. Spatial domain methods directly operate on the pixels. Spatial domain processes could be denoted by the following expression:

$$g(x,y) = T[f(x,y)] \quad (1)$$

where $f(x,y)$ and $g(x,y)$ are the input and processed output images respectively. T is an operator on f which is defined

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over some neighborhood of (x, y) or over a set of images [1].

When T operates over the considered pixel only or the neighborhood size is $[1 \times 1]$ then it is called point processing. Here, the output g purely depends on the value of f at location (x, y) and T becomes a gray-level or intensity transformation/mapping function of the form:

$$s = T(r) \tag{2}$$

where s and r are denoting the gray level of $f(x, y)$ and $g(x, y)$ at location (x, y) respectively. For example, contrast stretching, image negative, power-law transformation, image thresholding for creating binary images and so on which are very simple, yet powerful, image processing techniques which could be devised using this point processing based gray level transformations [1].

The enhancement techniques which are discussed so far they don't consider the overall appearance of the image. They simply provide transformation of a certain intensity value and according produces the output intensity value. Histogram Equalization (HE) is most common and popular technique which takes care of the global appearance of the image [5]. Histogram represents the plotting of number of pixels against each intensity value. It basically tells about the probability of occurrence of a pixel having one specific intensity and gives information of global appearance of an image [6]. In HE method the pixels are well distributed over the full dynamic intensity range. Basically HE computes linear cumulative histogram of the original image and dispenses intensity values over its dynamic intensity range. HE based techniques have been used in medical image processing, satellite image processing etc. There are two types of HE methods: (a) Global HE method, (b) Local HE method [1]. Global HE method carries out modification of the pixels by the transformation function based on the gray-level content of an entire image. The distribution of the intensity levels are normalized by quantizing the Cumulative Density Function (CDF) obtained after calculating the Probability Density Function (the ratio of the pixels in a particular intensity level to the total number of pixels in the image) so that the output image may have a linear distribution of intensity levels. This global aspect is appropriate for overall enhancement of the image, but there may be some cases in which it is necessary to enhance the details over local areas in an image. In those cases this very procedure fails to preserve the brightness and contrast features locally. In case of Local HE, the neighbourhood pixels are considered for equalization by using their histogram intensity statistics. The original image is divided into various sub-blocks in the form of square or rectangular neighbourhood. At each location, the histogram of the points in the neighbourhood is computed and either a histogram equalization or histogram specification transformation function is obtained. Then after repeating these steps finally the resultant image is obtained by merging the sub-blocks which results in the creation of several unwanted artifacts all over the image known as checkerboard effect. Histogram specification (HS) is a generalized version of histogram equalization where output image associated with a particular histogram that could be subjectively specified. It is basically consists of three steps: (1) Equalization of the input histogram, (2) equalization of the specified histogram (3) relate the two equalized histograms. HS is practically helpful to compress the dynamic range of the image which removes the pixel values that contain too less information.

When the size of the neighborhood increases form $[1 \times 1]$ then it allows more flexibility to develop image processing approaches and the value of $g(x, y)$ significantly depends on the values of f in a predefined neighborhood of (x, y). One of the primary approaches in this formulation is based on the use of masks (also referred to as filters, kernels, templates, or windows) [1]. Fundamentally, a mask is a small (suppose, 3×3) 2-D array in which the values of the mask coefficients determine the nature of the process, such as image sharpening. Enhancement techniques based on this type of approach often are referred to as mask processing or filtering [1]. Besides these methods, mask/filter based techniques are also very popular and effective for the several kinds of image processing tasks such as noise removal based image enhancement, an edge detection based image enhancement etc. There are three different types of operation under this mask processing technique namely (1) Smoothing filter, (2) Median filter, (3) Sharpening filter.

Image smoothing is a spatial filtering operation where the value of at particular location say, (x, y) in the processed image is the average of all the pixel value in the neighborhood of (x, y). This averaging filter is also called lowpass filter.

The median filter is a nonlinear filter where the median value of neighbor certain pixel (x, y) is used to replace some specific pixel. In this kind of filtering operation, the noise in the output image almost vanishes but at the same time the contrast and sharpness of the image more or less intact. This is the main advantage of median filtering rather than averaging filtering.

Sharpening spatial filter is used to highlight the intensity or variation details in an image. In previous cases averaging or smoothing over an image is done and due to that, the image becomes blur and the details in the image are lost. This smoothing operation is like integration operation. So the derivative operations are used for sharpening of an image. One can use 2 types of derivative operation namely first order derivatives and second-order derivatives. The first order derivatives produce a thicker edge and the second order derivatives give a stronger response to finding the thin line and isolated point. So the second order derivative is better in image enhancement. For example, Sobel operator is developed based on first-order derivative whereas Laplacian operator is the second-order derivative based operation.

Besides these techniques, Contrast Stretching (CS) is widely used method in image processing for improving the contrast of an image by 'stretching' its intensity range to a desired or permissible one. It equalizes the contrast all over the image by simultaneously adjusting each gray value at the darkest and lightest portions. In that way, it helps visualize the details and structure of the very light or dark regions [7]. Its main capability is that it applies a linear scaling function only. Before to stretching, it is also necessary to specify the lower and upper pixel value limits in which CS will stretch the image.

Literature reports that NIOAs are significantly used in spatial domain for image enhancement. Beside that Wavelet and Fourier domain are also used. Most importantly these transform based domains are used for the denoising based image enhancement purpose [8]. Fourier [2], Hartley [2], cosine [2], Hadamard [2], Wavelet [3, 9], Curvelet [4, 8] transforms are widely used for the image enhancement field. This study also reports the application of NIOAs based image enhancement models in these transform based domains.

Colour image which is nothing but a digital image with colour information is also considered in this study. To facilitate the specification of colours in some standard and general way, colour model/colour space/colour system is very necessary [1]. A colour model is a specification of a coordinate system and a subspace within that the system where each colour is represented by a single point [1]. Some well-known colour spaces are RGB (Red–Green–Blue), CMY (Cyan–Magenta–Yellow), CMYK (Cyan–Magenta–Yellow–Black), HSI (Hue–Saturation–Intensity), HSV (Hue–Saturation–Value), YUV, YCbCr, CIELAB etc. [1]. The literature also reports colour image enhancement techniques which are given below.

Several gray level image enhancement methods have been discussed in literature such as Histogram Equalization (HE), Linear Contrast Stretching (LCS) and so on. However, generalizing any gray level contrast enhancement method for colour image is not an easy task. There are several factors associated with the colour image such as Hue, saturation and intensity [1, 10]. Hue represents the kind of colour i.e. the dominant wavelength that exists in mixture of colours [1, 10]. Saturation is the measurement of the purity of the colour [1, 10] and Intensity components represent non-chromatic information. Hue is one of the most sensitive factor that needs to be taken care at the time of enhancement as the changing of hue of any pixel means changing of the corresponding colour of that pixel. Therefore, the main aim of image enhancement is to improve the visual quality of an image without distorting the corresponding hue. Some colour image enhancement methods exist in literature, which are discussed as follows.

A saturation component based colour image enhancement method had been proposed by Strickland et al. [11]. Improvement of this method had been done by Thomas et al. [12] by considering the correlation between luminance and saturation components. A joint equalization method based on intensity and saturation component had been developed by Pitas [13]. A hue preserving method was proposed by Weeks et al. [14] by modifying both saturation and intensity component in colour difference (C–Y) space. A 3-D histogram specification algorithm [15] and one 3-D colour histogram equalization [16] methods were also reported in literature. Histogram explosion, a multivariate enhancement technique had been proposed by Mlsna and Rogriguez [17]. The same author also extended the same strategy for the CIE LUV space [18]. Kong and Ibrahim [19] successfully employed the Brightness Preserving Dynamic Histogram Equalization (BPDHE) method for colour images by using different colour spaces. Different colour spaces based colour equalization method had been proposed by Bockstein [20] and successfully applied to colour images. Shyu and Leou [21] proposed a Genetic Algorithm (GA) based colour image enhancement model. Yang and Rodriguez [22] proposed two hue preserving methods known as scaling and shifting to modify the luminance and saturation components. Basically, colour co-ordinates transformation need not to be required to develop these two methods i.e. scaling and shifting. Raju and Nair [23] developed one HSV space based colour image enhancement model which was not free from gamut problem. The above discussed algorithms though are effective for enhancement purpose, but most of them do not take care of the gamut problem as a result after enhancement the pixels values of the RGB components do not lay within their respective intervals [10]. This gamut problem mainly occurs due to the conversion of colour spaces with modified intensity and saturation components [10]. Clipping is one of the general strategies to remove this gamut problem [10, 14, 22]. But clipping creates undesired shift of hue [10, 11]. Normalization is another technique to handle this as it does not change the hue but reduces some of the achieved intensities [10, 21]. Shyu used normalization to tackle the gamut problem [21]. Naik and Murthy [10] developed one hue preserving and gamut problem free colour image enhancement model in RGB and CMY colour spaces. Gorai and ghosh [24] also developed a hue preserving and gamut problem free colour image enhancement method with the help of HSI and RGB spaces. Dhal and Das [25] also proposed Hue Preserving

Colour Image Enhancement Models in RGB Colour Space without Gamut Problem. They developed three modified colour models based on HSI, HSV and YUV colour spaces which are hue preserving and gamut problem free. Any gray level image enhancement techniques could be applied through these colour models efficiently. HSV based colour model outperformed developed HSI, YUV models and also gave superior results to the well-known existing eHSI [26] and Naik's [10] colour models visually and mathematically. Chien and Tseng [26] proposed one gamut problem free hue preserving colour image enhancement model known as exact HSI (eHSI) model. By along with the models of Naik and Murthy [10], Gorai and Ghosh [24], Chien and Tseng [26] any gray level image enhancement method can be successfully applied for colour image and also these models are gamut problem free. Therefore, it can be said that there are three main ways through which colour image can be enhanced:

1. By scaling and shifting the colour components of the traditional colour space which is not hue preserving and gamut problem free.
2. By employing any gray level image enhancement techniques over luminance component and/or saturation components of the traditional colour spaces which is hue preserving but not gamut problem free.
3. By employing any gray level image enhancement techniques over luminance component of the derived colour models which is hue preserving and also gamut problem free.

2 Major Challenges in Image Enhancement

There are lots of problems in the field of pattern recognition and image processing, where efficient search have to be performed in complex spaces in order to attain an optimal solution [27]. One such problem is contrast enhancement of images which improves the picture quality, more specifically, to improve the quality for visual analysis and/or machine understanding. There is no unique measure to quantitatively judge the quality of a given image enhancement operator or transformation function. It is also not clear which measure is to be used for a specific type of images or for a specific image [27]. Automatic enhancement is a process to yield enhanced images without human (subjective) intervention, is an extremely complicated job in image processing [28, 29]. This is because automatic enhancement needs to specify an objective criterion for enhancement while evaluating the quality of an image is done finally by the human interpreter. Most of the enhancement techniques existent to date are empirical methods, dependent on the particular type of image [1, 28]. More important, these techniques require interactive procedures to obtain satisfactory results and therefore are not suitable for routine application [28]. Therefore, the major challenges of image enhancement are as follows:

1. Selection of a proper transformation/mapping function (operator) for achieving a required output. Generally, a suitable nonlinear functional mapping is employed to perform this job.
2. Efficiency increment of the simple transformation functions for acquiring a proper enhanced image within a reasonable time and use of the same transformation function to satisfy the different needs of the users is also a great challenge. In other words, is it possible to use the same transformation function for enhancing the quality of an image according to the need of the mid/high-level image processing techniques such as segmentation, object recognition etc. In the case of parameterized transformation functions, accurate parameter setting significantly affects the performance of the considered transformation function. But, proper parameter setting is very time consuming and experience based. Manual parameter setting also does not impart fully automation power to the image enhancement model.
3. Selections of an evaluation function to define a quantitative measure of an enhanced image.
4. Employment of different gray level image enhancement techniques for enhancing the colour images is a great challenging task. Therefore, developments of different colour models are also necessary through which any gray level image enhancement technique could be applied for colour image.

Every kind of nonlinear function will not able to generate a required (meaningful) enhanced version of an image [27, 30]. For a specific image, it is difficult to opt for a functional form which will be appropriate without prior knowledge of the image statistics. Even with the prior knowledge of the image statistics, it is sometimes probable only to approximate function required for enhancement [27, 30, 31]. The choice of the accurate functional form still requires human interaction in an iterative process. For making the image quality evaluation process objective, it is essential to define an objective function which will provide a quantitative measure for enhanced image's quality. Entropy, Edge pixels, compactness, index of area coverage (IOAC), Divergence etc. are well-known evaluation functions available in the literature to measure automatically the quality of the enhanced image [27]. It has also been observed that all these measures are suitable for some kinds of images.

Recently, the image enhancement problem is formulizing as nonlinear and multi-modal optimization problem to overcome the above discussed issues. To solve these non-linear and multi-modal problems, Nature-inspired Optimization Algorithms (NIOA) are widely used in literature. The discussion over NIOAs and their classification are given below.

3 Classes of Nature-Inspired Optimization Algorithms

Currently, numerous nature-inspired optimization algorithms (NIOA) have been developed by imitating the behavior of natural and biological systems [32]. These algorithms are also called nature-inspired metaheuristic algorithms (NIMA) [33, 34]. Heuristic algorithms use a trial-and-error approach in generating new solutions, whereas metaheuristic algorithms are a higher-level heuristics with the use of memory, solution history and other forms of 'learning' strategy [34]. Literature also demonstrates that the recent trends are to name all stochastic algorithms with randomization and local search as 'metaheuristic' [35–37]. As they used these features of metaheuristic algorithms, they are also called nature-inspired metaheuristic algorithms (NIMA). Compare to traditional algorithms, NIOA is generally developed for global search. They have the following merits and features [34]:

(a) NIOA have the capability for finding the true global optimality as they are global optimizers.
(b) They work over a wider range of problems without the assistance of specific knowledge because they treat the problems as a black-box.
(c) NIOA or NIMA could deal with highly nonlinear, multimodal problems with discontinuity because they are generally gradient-free methods.
(d) These algorithms have the stochastic components in terms of random numbers and random walks. Therefore, no similar solution will be obtained, even starting with the identical initial points, unlike traditional deterministic algorithms. Due to that stochastic component, these algorithms able to escape from local minima (so less chance to trap/stuck into local minima).
(e) Although NIOA is a global optimizer, they have the balanced global search (exploration) and local search (exploitation) components for finding the optimal solution. Global search or exploration signifies the visiting of a new region in a search space. Whereas, local search (exploitation) indicates the visiting of new neighborhood regions of a previously visited point. But the balance between exploration and exploitation can further be increased by using different strategies.

Due to these features, NIOAs are very much powerful and efficient for solving several classes of real-world problems which are NP-Hard. A problem is NP-Hard when increasing the problem size causes an increase in the time complexity exponentially (mathematically described as $O(2^n)$, where n denotes the problem size) [38, 39].

4 Classification of These Nature-Inspired Optimization Algorithms (NIOA)

These algorithms are called nature-inspired because researchers have developed them under the inspiration of different natural phenomenon. Depending on the different source of inspiration from nature, these NIOA are broadly classified into some classes recently which are (a) Evolutionary Algorithms (EA), (b) Biology-inspired or Bio-inspired algorithms, (c) Physics and Chemistry based algorithms, (d) Other algorithms. The different classes of NIOA are represented as Fig. 1 from the set theory based point of view. The brief overview about these classes of optimization algorithms are as follows:

(a) *Evolutionary Algorithms (EA)* EA imitates the Darwinian theory of evolution [38, 40]. They have the following components: Population of individuals and their representation, fitness function for evaluating the individuals, parent selection mechanism, different operators such as crossover and mutation, survivor selection mechanism (replacement) and the initialization and termination condition mechanisms. EA is also divided into the following major classes [38]:

    (1) Genetic Algorithm (GA), (2) Evolution Strategies (ES), (3) Genetic Programming (GP), (4) Evolutionary Programming (EP) and (5) Differential Evolution (DE). GA which was invented by John Holland in 1975 [181, 182] use the binary representation of individuals. Whereas, ES [176, 177] and DE [173–175] use real-valued representation of individuals. ES and DE also use mutation and crossover operators like GA. In GP [183, 184], an individual is represented as a program rather than real numbers. But, in EP [178–180], individuals are finite state machine (FSM) which consists of a number states and state transition. The similarities and dissimilarities among the classes of EA are given as Fig. 2 [33].

(b) *Biology-Inspired or Bio-inspired Algorithms* the Greater part of nature-inspired algorithms is

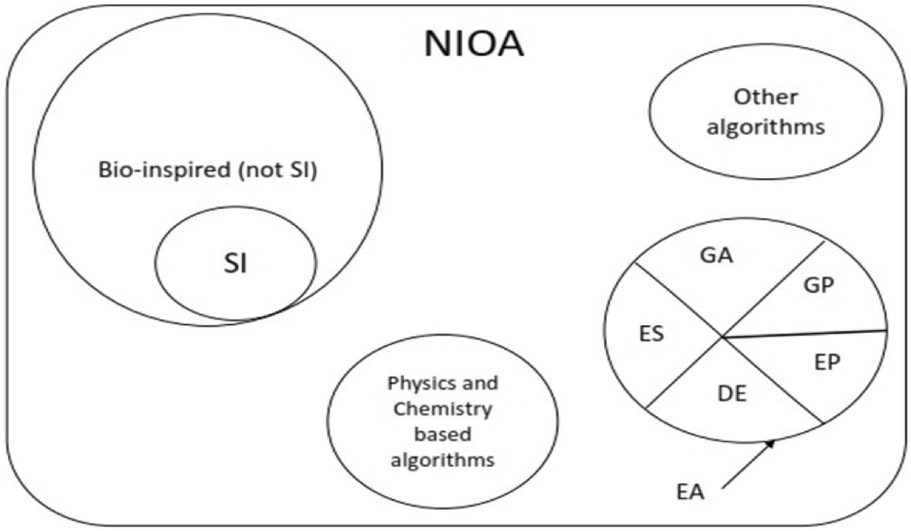

Fig. 1 The relationship between the classes of NIOA in terms of set theory

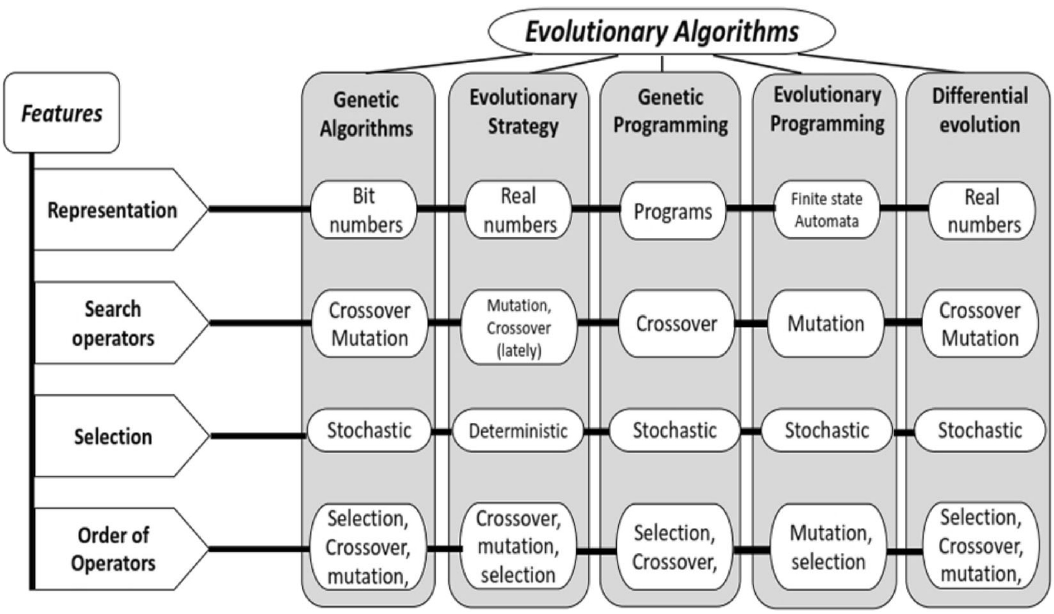

Fig. 2 Similarities and dissimilarities among the classes of EA

developed based on some good characteristics of the biological system. Hence, the major part of nature-inspired algorithms is biology-inspired, or bio-inspired for short [32]. These bio-inspired algorithms are also subdivided into two major sub-classes: (i) Swarm Intelligence (SI) based algorithms, (ii) Bio-inspired but not swarm intelligence based.

(1) *Bio-inspired but Swarm Intelligence (SI) Based Algorithms* Swarm intelligence (SI) has been developed by considering the collective, promising behavior of various interacting agents who follow some straightforward rules. All SI-based algorithms are multi-agents/population-based, inspired by the collective behavior of social insects such as ants, firefly, and bees, as well as from other animal societies like flocks of birds or fish such as cuckoo, bat etc. Many algorithms have been developed by drawing inspiration from swarm-intelligence systems in nature. For example, Particle Swarm Optimizer (PSO) is developed based on the swarming behavior of fish and birds, Firefly Algorithm (FA) is developed based on the flashing behavior of swarming fireflies, Cuckoo search (CS) is developed by considering the brooding parasitism of some cuckoo species, whereas Bat

Algorithm (BA) uses the echolocation of foraging behavior of bats. Ant colony optimization (ACO) uses the interaction of social insects (e.g., ants), whereas the class of bee algorithms are all developed based on the foraging behavior of honey bees such as Artificial Bee colony (ABC) algorithm. SI-based algorithms are among the most successful and generally employed NIOA. The reasons behind such success are this class of algorithms generally share information among individuals of the population, so that self-organization, co-evolution, and learning during the searching time could assists to provide better optimal results. Another reason is that as they used the population of individuals which can be parallelized without any difficulty and as a result of it, large-scale optimization becomes more practical from the implementation point of view.

(2) *Bio-inspired but Not SI Based Algorithms* Algorithms belong to this class are not following directly the swarming behavior. Therefore, they are called Bio-inspired but not SI based. These algorithms are also very effective to solve multimodal and highly nonlinear optimization algorithm because they are multiagent/population-based algorithms like SI, where, individuals also share information among each other. For example, the Flower Pollination Algorithm (FPA) [41] is a Bio-inspired algorithm, but not an SI based because FPA has been developed by mimicking the pollination features of flowering plants and the associated flower consistency of some pollinating insects. Other well-known algorithms belong to this class are Biogeography-based optimization (BBO), Invasive weed optimization (IWO) etc. Therefore, from the view of set theory, it can be said that SI is a subset of Bio-inspired which is a subset of NIOA. Figure 1 demonstrates the relationship between these classes of NIOA.

(c) *Physics and Chemistry Based Algorithms* These kinds of algorithms are developed inspired by the resources of physics and chemistry such as certain physical and/or chemical laws or a phenomenon like electrical charges, gravity etc. and so that they are not the subset Biology-inspired/bio-inspired algorithms. Simulated Annealing (SA), Harmony Search (SA), Gravitational Search Algorithm (GSA), Big bang-big Crunch (BBBC) belongs to the physics and chemistry class.

(d) *Other Algorithms* Recently some optimization algorithms have been developed by using some different characteristics such as emotional, social etc. which are not bio-inspired or physics chemistry based. Therefore these algorithms are categorized into other class. Some example of these algorithms is Differential search algorithm, Social–emotional optimization, League championship algorithm etc.

Table 1 represents the class wise names of NIOAs, their abbreviations, year of invention and the inventor. Figure 3 represents the developments of different NIOAs over the last five decades. It can be easily seen that the majority of NIOAs are developed in between 2000 and 2017. In this period of 17 years, 105 NIOAs are invented where the total numbers of NIOAs are 132 according to best of our knowledge which is listed in Table 1. Thus there is a sudden increment in that period or the golden era of NIOAs. The Fig. 3 also reveals that the numbers of NIOAs development increases rapidly since the year 2000. This growth of the NIOAs is not is not a good sign in this novel research field according to Fister et al. [42]. Fister et al. gave a good example by writing that there are about 28,000 living species of fish, this cannot mean that researchers should develop 28,000 different algorithms based on fish. Majority of the four classes (i.e. EA, Bio-inspired, physics/chemistry, and others) of NIOAs are also investigated and presented as Fig. 4. Figure 4 demonstrates that 32% of NIOAs belong to Bio-inspired algorithms which are SI based, 24% are Bio-inspired algorithms but not SI based, 25% are physics/chemistry based, 15% belongs to others class and 4% are EAs. Therefore, it can be concluded that most algorithms are devised based on the resources of biology and that's why greater than 50% NIOAs belongs to bio-inspired based class. But it is also a bitter truth that EA-based algorithms are not designed by the researchers. Resources of physics and chemistry are also played vital role in developing such new optimization algorithms. Majority of the algorithms belong to "others" class is also good. It is also true that the resources of nature are too diverse. Researchers should follow these resources to create algorithms but these algorithms should be effective and developed by satisfying some criteria formulated by of Yang [32, 43]. According to Yang et al. [32, 43] the previous statement can be expressed mathematically by the following expression:

$$(x_1, x_2, \ldots, x_n)^{t+1} = AL\left[\left((x_1, x_2, \ldots, x_n)^t\right); \ldots; (p_1, p_2, \ldots, p_m); (rw_1, rw_2, \ldots, rw_k)\right] \tag{3}$$

This expression states that algorithm AL attempts to find better solution $(x_1, x_2, \ldots, x_n)^{t+1}$ at (t + 1)th iteration form

Table 1 Names of NIOAs based on their classes

	Biology-inspired or Bio-inspired algorithms			
	Algorithms	Author	Year	References
(a) Bio-inspired (swarm intelligence based) algorithms				
1.	Ant colony optimization (ACO)	Dorigo	1992	[46]
2.	Ant lion optimization algorithm (ALO)	Mirjalili	2015	[47]
3.	Artificial bee colony (ABC)	Karaboga and Basturk	2007	[48]
4.	Artificial swarm intelligence (ASI)	Rosenberg	2014	[49]
5.	Bacterial foraging (BFOA)	Passino	2002	[50]
6.	Bacterial-GA foraging (BFO-GA)	Chen et al.	2007	[51]
7.	Bat algorithm (BA)	Yang	2010	[52]
8.	Bee colony optimization (BCO)	Teodorovic and Dell	2005	[53]
9.	Bee Hive (BH)	Wedde et al.	2004	[54]
10.	Bee system (BS)	Lucic and Teodorovic	2001	[55]
11.	Bees algorithms	Pham et al.	2006	[56]
12.	Bees swarm optimization (BSO)	Drias et al.	2005	[57]
13.	Bumblebees (BBA)	Comellas and Martinez	2009	[58]
14.	Cat swarm (CSO)	Chu et al.	2006	[59]
15.	Consultant-guided search (CGS)	Iordache	2010	[60]
16.	Crow search algorithm (CSA)	Askarzadeh	2016	[61]
17.	Cuckoo search (CS)	Yang and Deb	2009	[62]
18.	Dragonfly algorithm (DA)	Mirjalili	2016	[63]
19.	Dynamic virtual bats algorithm (DVBA)	Topal and Altun	2014	[64]
20.	Eagle strategy (ES)	Yang and Deb	2010	[65]
21.	Fast bacterial swarming algorithm (FBSA)	Chu et al.	2008	[66]
22.	Firefly algorithm (FA)	Yang	2010	[67]
23.	Fish swarm school (FSS)	Li et al.	2002	[68]
24.	Glowworm swarm optimization (GSO)	Krishnanand and Ghose	2005, 2009	[69, 70]
25.	Good lattice swarm optimization (GLSO)	Su et al.	2007	[71]
26.	Grasshopper optimisation algorithm	Saremi et al.	2017	[72]
27.	Grey wolf optimizer (GWO)	Mirjalili et al.	2014	[73]
28.	Hierarchical swarm model (HSM)	Chen et al.	2010	[74]
29.	Hunting search (HS)	Oftadeh et al.	2009	[75]
30.	Killer whale optimization (KWO)	Biyanto et al.	2017	[76]
31.	Krill herd (KH)	Gandomi and Alavi	2012	[77]
32.	Monkey search (MS)	Mucherino and Seref	2007	[78]
33.	Moth-flame optimization algorithm (MFBO)	Mirjalili	2015	[79]
34.	Particle swarm algorithm (PSO)	Kennedy and Eberhart	1995	[80]
35.	Salp swarm algorithm (SSOA)	Mirjalili et al.	2017	[81]
36.	shark smell optimization (SMO)	Abedinia et al.	2016	[82]
37.	Sheep shepherding algorithm (SSA)	Kim et al.	2016	[157]
38.	Virtual ant algorithm (VAA)	Yang	2006	[83]
39.	Virtual bees (VBA)	Yang	2005	[84]
40.	Weightless swarm algorithm (WSA)	Ting et al.	2012	[85]
41.	Whale optimization algorithm (WOA)	Mirjalili and Lewis	2016	[86]
42.	Wolf search (WSO)	Tang et al.	2012	[87]
(b) Bio-inspired (not swarm intelligence based) algorithms				
43.	Atmosphere clouds model (ACM)	Yan and Hao	2013	[88]
44.	Biogeography-based optimization (BBO)	Simon	2008	[89]
45.	Brain storm optimization (BSO)	Shi	2015	[90]

Table 1 (continued)

	Biology-inspired or Bio-inspired algorithms			
	Algorithms	Author	Year	References
46.	Cuttlefish algorithm (CFA)	Eesa et al.	2013	[91]
47.	Dolphin echolocation (DEA)	Kaveh and Farhoudi	2013	[92]
48.	Duelist Algorithm (DA)	Biyanto et al.	2016	[93]
49.	Ecogeography-based optimization (EBO)	Zheng	2014	[94]
50.	Eco-inspired evolutionary algorithm (EIEA)	Parpinelli and Lopes	2011	[95]
51.	Egyptian vulture (EVOA)	Sur et al.	2013	[96]
52.	Fish-school search (FSS)	Bastos Filho et al.	2008, 2009	[97, 98]
53.	Flower pollination algorithm (FPA)	Yang	2012, 2013	[41, 99]
54.	Gene expression programming (GEP)	Ferreira	2001	[100]
55.	Great salmon run (GSR)	Mozaffari	2012	[101]
56.	Group search optimizer (GSO)	He et al.	2009	[102]
57.	Human-inspired algorithm (HIA)	Zhang et al.	2009	[103]
58.	Invasive weed optimization (IWO)	Mehrabian and Lucas	2006	[104]
59.	Japanese tree frogs calling (JTFC)	Herńandez and Blum	2012	[105]
60.	Lion optimization algorithm (LOA)	Yazdani and Jolai	2016	[106]
61.	Marriage in honey bees (MHB)	Abbass	2001	[107]
62.	Neuronal communication (NC)	Gharebaghi and Ardalan	2017	[108]
63.	Opt bees (OBA)	Maia et al.	2012	[109]
64.	Paddy field algorithm (PFA)	Premaratne et al.	2009	[110]
65.	Queen-bee evolution (QBE)	Jung	2003	[111]
66.	Roach infestation algorithm (RIA)	Havens	2008	[112]
67.	Shuffled frog leaping algorithm (SFLA)	Eusuff and Lansey	2003	[113]
68.	Sperm whale algorithm (SWA)	Ebrahimi and Khamehchi	2016	[114]
69.	Spotted hyena optimizer (SHO)	Dhiman and Kumar	2017	[115]
70.	Swine flow optimization algorithm (SFOA)	Pattnaik et al.	2013	[116]
71.	Symbiotic organisms search (SOS)	Cheng and Prayogo	2014	[117]
72.	Termite colony optimization (TCO)	Hedayatzadeh et al.	2010	[118]
73.	Virulence optimization algorithm (VOA)	Jaderyan and Khotanlou	2016	[119]
74.	Virus colony search (VCS)	Li et al.	2016	[120]
Physics and chemistry based algorithms				
75.	Bayesian optimization algorithm (BOA)	Pelikan	2005	[121]
76.	Big bang-big crunch (BBC)	Zandi et al.	2012	[122]
77.	Black hole (BH)	Hatamlou	2013	[123]
78.	Central force optimization (CFO)	Formato	2007	[124]
79.	Charged system search (CSS)	Kaveh and Talatahari	2010	[125]
80.	Chemotherapy Science algorithm(CSA)	Salmani and Eshghi	2017	[126]
81.	Colliding bodies optimization (CBO)	Kaveh and Mahdavi	2014	[127]
82.	Electro-magnetism optimization (EMO)	Cuevas et al.	2012	[128]
83.	Fractal-based algorithm (FBA)	Kaedi	2017	[129]
84.	Galaxy-based search algorithm (GBSA)	Shah-Hosseini	2011	[130]
85.	Gravitational search (GSA)	Rashedi et al.	2009	[131]
86.	Harmony search (HS)	Geem et al.	2001	[132]
87.	Hydrological cycle algorithm (HCA)	Wedyan et al.	2017	[133]
88.	Intelligent water drop (IWD)	Hosseini	2007	[134]
89.	Ions motion algorithm (IMA)	Javidy et al.	2015	[135]
90.	Mass and energy balances algorithm (MEBA)	Biyanto et al.	2017	[136]
91.	Optics inspired optimization (OIO)	Kashan	2015	[137]

Table 1 (continued)

	Biology-inspired or Bio-inspired algorithms			
	Algorithms	Author	Year	References
92.	Rain water algorithm (RWA)	Biyanto et al.	2017	[138]
93.	Rain-fall optimization algorithm (RFOA)	Kaboli et al.	2017	[139]
94.	River formation dynamics (RFD)	Rabanal et al.	2007	[140]
95.	Self-driven particles (SDP)	Vicsek	1995	[141]
96.	Simulated annealing (SA)	Kirkpatrick et al.	1983	[142]
97.	Simulated raindrop algorithm (SRA)	Ibrahim, et al.	2014	[143]
98.	Sine cosine algorithm (SCA)	Mirjalili	2015	[144]
99.	Sonar inspired optimization (SIP)	Zanetos and Dounias	2017	[145]
100.	Spiral optimization (SO)	Tamura and Yasuda	2001	[146]
101.	Stochastic difusion search (SDS)	Bishop	1989	[147]
102.	Thermal exchange optimization (TEO)	Kaveh and Dadras	2017	[148]
103.	Vision correction algorithm (VCA)	Kim et al.	2016	[157]
104.	Vortex search algorithm (VSA)	Doğan and Ölmez	2015	[149]
105.	Water cycle algorithm (WSA)	Eskandar et al.	2012	[150]
106.	Water wave optimization (WWO)	Zheng	2015	[151]
107.	Weighted attraction method (WAM)	Friedl and Kuczmann	2015	[152]
Other algorithms				
108.	Adaptive dimensional search (ADS)	Hasançebi and Azad	2015	[153]
109.	Anarchic society optimization (ASO)	Shayeghi and Dadashpour	2012	[154]
110.	Artificial cooperative search (ACS)	Civicioglu	2013	[155]
111.	Backtracking optimization search (BOS)	Civicioglu	2013	[156]
112.	Cancer treatment algorithm (CTA)	Kim et al.	2016	[157]
113.	Cohort intelligence (CI)	Kulkarni et al.	2017	[33]
114.	Differential search algorithm (DSA)	Civicioglu	2012	[158]
115.	Elitist self-adaptive step-size search (ESASS) algorithm	Azad and Hasançebi	2014	[159]
116.	Football game inspired algorithm (FGIA)	Fadakar and Ebrahimi	2016	[160]
117.	Grammatical evolution (GE)	Ryan et al.	1998	[161]
118.	Guided stochastic search (GSS)	Azad et al.	2014	[162]
119.	Imperialist competitive algorithm (ICA)	Atashpaz-Gargari and Lucas	2007	[163]
120.	League championship algorithm (LCA)	Kashan	2009	[164]
121.	Passing vehicle search (PVS)	Savsani and Savsani	2016	[165]
122.	Search group algorithm (SGA)	Gonçalves et al.	2015	[166]
123.	Social emotional optimization (SEO)	Xu et al.	2010	[167]
124.	Tabu search (TS)	Fred Glover	1989, 1990	[168, 169]
125.	Teaching–learning-based optimization (TLBO)	Rao et al.	2012	[170]
126.	World cup optimization (WCO) algorithm	Razmjooy et al.	2016	[171]
127.	Yin-Yang-pair optimization (YYPO)	Punnathanam and Kotecha	2016	[172]
Evolutionary algorithms				
128.	Differential evolution (DE)	Price	1999, 2005, 1997	[173–175]
129.	Evolution strategies (ES)	Beyer, Michalewicz	2002, 1996	[176, 177]
130.	Evolutionary programming (EP)	Back, Fogel, Yao	1997, 1993, 1999	[178–180]
131.	Genetic algorithm (GA)	Holland	1975	[181, 182]
132.	Genetic programming (GP)	Koza	1992, 1994	[183–185]

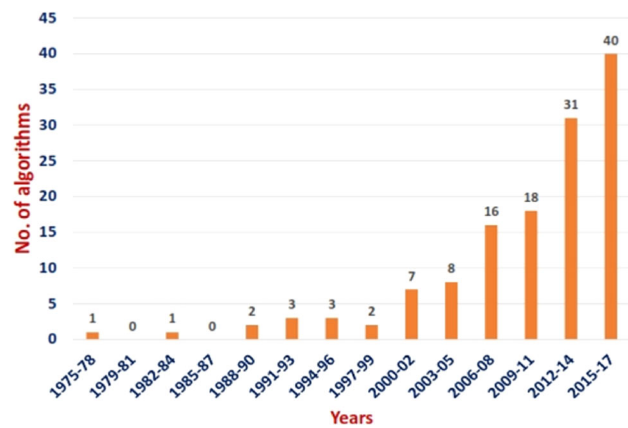

Fig. 3 Year wise development of NIOAs

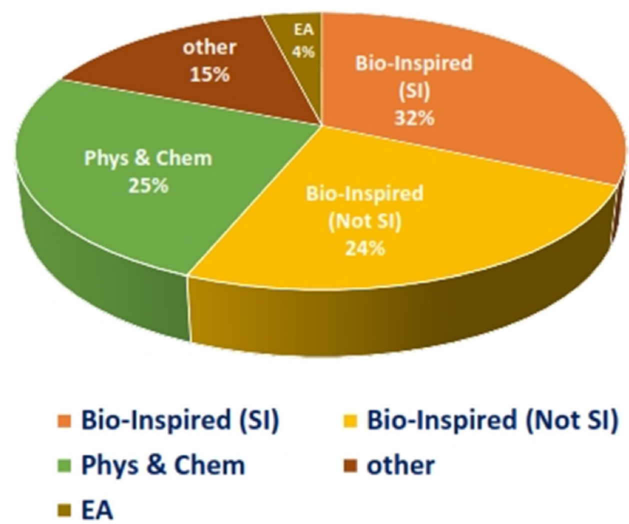

Fig. 4 Majority of different classes of NIOAs

the current iteration t by using the algorithm associated parameters $(p_1, p_2, \ldots, p_m)$ and some kind of random numbers $(rw_1, rw_2, \ldots, rw_k)$. Several kinds of random number generators can be used to generate $(rw_1, rw_2, \ldots, rw_k)$. But which random number generator is better? A short answer of this question is that it is basically problem and used algorithm oriented. Although all the discussed and listed algorithms follow this expression but it is difficult to analyze the behavior of such algorithms because this expression can be highly nonlinear [32]. Some techniques such as Markov chains theory, Dynamical system theory could explain these algorithms to some extent. But, the detailed mathematical framework is still under development. Other side, it is a big statement that one algorithm is better than others. According to No Free Lunch (NFL) theorem, if one algorithm is superior on one class of problems, it does not signify that it will also be superior on the other classes of problems [44, 45]. Therefore, the efficacy and supremacy of one NIOA over others is problem dependent. But, it is also true that algorithm design perspective has great impact over the effectiveness of any kind of algorithm and NIOA are also no exception to that. Therefore, it can be seen that some NIOA are imperfectly designed in terms of some basic capabilities like the mixing and diversity among the individuals, good balance between exploration and exploitation search abilities etc. compares to the efficient algorithms which have the both mixing and diversity among individuals and exploitation search abilities through which they can able to explore and exploit the immense search space efficiently. Some examples of efficient algorithms are Particle Swarm Optimization, Differential Evolution, Cuckoo Search and Firefly Algorithm which have proved their effective performance over diverse optimization fields.

4.1 Characteristics of NIOA

The detailed characteristics/components of NIOAs and their roles are listed in Table 2. But, from the general perspective, each NIOA has three major characteristics which are: (a) exploration and exploitation, (b) adaption and diversity, and (d) key operators. The components listed in Table 2 are always facilitated these three major characteristics.

(a) *Exploration and Exploitation* Whether local search (exploitation) or global search (exploration), all determined by the two factors: actual search mechanisms within an algorithm and the structure of the concerned algorithm [186]. Therefore, there is a trade off between exploration and exploitation. But, a well balance is essential for achieving the good performance. More exploitation and less exploration signifies the system can converge more rapidly, but the chance of reaching the true global optimal point could be little. Conversely, too less exploitation and too more exploration could be the reason of the very slow convergence. The optimal balance represents the accurate quantity of exploration and exploitation, which may lead to the optimal performance of an algorithm. But, the balance is problem and algorithm's structure dependent and therefore, it is a great challenging task.

(b) *Adaption and Diversity* Each NIOA has the adaption and diversity characteristics which are associated with the considered algorithm in different forms. For example, the different ways to balance between exploration and exploitation is the most important form of adaption [186, 187]. Then varying the population size is also one kind of adaption so that the algorithm gives a best overall performance. Tuning the algorithm's parameters are also adaption,

Table 2 Characteristics/components of nature-inspired optimization algorithms

Components of NIOAs	Role of the component
Population	It is a sampling technique which also maintains the diversity
Randomness	Get away from local minima. Performs the global as well as local search
Selection and elitism	Crucial components for convergence
Mutation, crossover, guidance of *gbest* solution, algorithmic formulas	Generate new solutions and their evaluation iteratively

which significantly increases the performance of the NIOAs. On the other hand, diversity can be associated with any NIOA in different forms such as the creation of a population of solutions with a good variation using randomization. Therefore, varying population size is adaption whereas creation of proper variation based population is a form of diversity. Thus adaption and diversity are internally correlated. As NIOAs are stochastic in nature, random variables are incorporated into them. These random variables based random walk are also very much responsible for maintaining the diversity component of the algorithm. Diversity reveals the population variance. If population variance is reaching to less value then diversity also decreases and the algorithm is going to converge. But, if diversity is reduced too quickly, premature convergence can take place. Therefore, a right amount of randomness and the right form of randomization can be crucial [186]. Therefore, it is true that both diversity and adaptation are very much important to certify the effectiveness of an algorithm. A population with better diversity is suitable for finding the global optimum by exploring the large space. Moreover, good adaption capability of an algorithm will facilitate it with good adjustment ability with an unknown problem and objective space under concerned. Therefore, this makes sure a potentially superior convergence than non-adaptive approaches [186].

(c) *Key Operators* NIOAs are also very sensitive to their key operators which control the diversity, balancing capability between exploration and exploitation etc. For example, well-known Genetic Algorithm (GA) has three major key operators: crossover (recombination), mutation and selection [186]. In GA, crossover and mutation are the processes of generating new solutions from the existing solutions. In crossover, two new solutions/individuals (offspring's) are produced from two existing solutions/individuals (parents) by swapping relevant/corresponding parts of their solutions. Whereas, the mutation has been performed on a single solution by altering a single site or multiple sites. But the selection is used to select the fittest solutions which mimic the main attribute of the Darwinian evolution in terms of the survival of the fittest. Basically, crossover could incorporate the exploration as well as exploitation into GA, whereas mutation mainly incorporates exploration. In addition to that selection offers a good exploitation power to an algorithm by selecting better solutions. Generally, improper selection may lead to a less convergent system. Thus, to develop a good variant of GA, more crossovers and less mutation have been performed typically. But the quantification of these key operators such as crossover and mutation is very much challenging task and future goal of these NIOAs based optimization fields. Different classes of algorithms have some key operators on which their performance is crucially dependent.

4.2 General Strategies for Efficiency Improvement of the NIOA

From the discussion of the above two sub-sections, it can be said that efficiency of the NIOA can be increased by a different strategy. Some common strategies are reported in the literature are as follows:

(a) *Parameter Adaption* Performance of a specific NIOA crucially depends on its algorithm-dependent Parameters. Adaptation can also occur to adjust these parameters. Literature proves that self-adaption or self-tuning of parameters is effective to improve the performance of any NIOA. But specifying the rules of self-adaption of these parameters are very problem and algorithm's structure dependent.

(b) *Random Numbers* How much randomness should be incorporated into an NIOA? It is a big question. Both experiential interpretation and simulation recommend that randomness may greatly facilitate the overall performance of NIOA. But it is difficult to say/prove the right degree of randomness which should incorporate into one specific algorithm. Literature reports several random number generators such as Uniform distribution, Normal or Gaussian distribution, Levy distribution, Chaotic maps, Random Sampling in Turbulent Fractal Cloud etc. which helps to incorporate the randomness into the NIOA [188]. This randomness significantly affects the efficacy of any NIOA. Literature proved that the supremacy of the random number generators solely depends on problem's types and algorithm's structure.

(c) *Hybridization* Hybridization among different NIOA of the same class or over different classes is one of the most common and powerful strategies to enhance the capability of NIOA. Hybridization permits the algorithms to introduce the problem specific information and it may also help to improve the balance between exploration and exploitation components of the considered hybrid algorithm [38, 189–191].

(d) *Communication and Sharing of Information Between Solutions* Algorithms like Cuckoo Search do not use the communication and sharing of individual's update information among each other [192, 193]. But this strategy significantly helps to increase the ability of any NIOA. It maintains the diversity among individuals and also balances the exploration and exploitation efficiency of the concerned algorithm. Using this strategy global best (*gbest*) solution crucially helps other solutions to find the optimal solution.

Other than these strategies, use of inertia weight [194, 195], initial population creation mechanism [196], efficient global and local search strategies [293, 297] also proved their significant applicability in NIOA field. Inertia weight is outstanding to maintain the population diversity and balance between exploration and exploitation.

4.3 General Framework of Nature-Inspired Optimization Algorithms and Their Components

One general framework of NIOA has been developed by considering the characteristics/components of the NIOAs. The step by step general framework is as follows:

Step 1 Creation of initial population of individuals randomly in most of the NIOA because they are multi-agent based system. Objective/fitness function also has been formulated to evaluate the individuals.
Step 2 Evaluating individual's fitness values and computes the global best (gbest) solution.
Step 3 The advancement/progression of the population of individuals is often obtained by some operations such as mutation, crossover, and selection of parents in the case of EAs; generate new solution towards global best (gbest) solution in the case bio-inspired and so on. Sometimes algorithmic formulas or equations are also used. Such progression is performed iteratively. During individual's evolution, they move around the search space randomly and new solutions are generated from them by using some randomization. This randomization incorporates the potential to escape from local minima. Basically, this step controls the balanced exploration and exploitation search of the concerned algorithm.
Step 4 Again the evaluation of fitness values of each individual has been performed for two perspectives: (a) selection of individuals for the next generation, (b) to find and store the global best (*gbest*) solution.
Step 5 Step 3 to step 4 repeated until the termination condition/stopping criterion.

Recently, NIOAs are widely used in the different fields of engineering such as structural optimization in civil engineering, scheduling and routing, software testing, data mining, image processing and so on [186]. In this paper, image enhancement problems are solved using NIOAs. Basically, the traditional algorithms such as simplex method and gradient-based methods are well known to all due to their nature of problem solving strategies and what types of problem they can solve. But, the selection of a specific NIOA over the large number of NIOAs is purely problem specific. One extensive experimental study should be performed to validate and test their performance over the considered problem. Prior knowledge or experience always plays a great role to develop one efficient optimization algorithm, but incorporating of the domain specific knowledge into optimization algorithms is still an ongoing challenging matter [186].

5 Single Objective Nature-Inspired Optimization Algorithms in Image Enhancement

Recently, image enhancements techniques have been formulated as optimization problems which show their complex and nonlinear behavior. Due to that efficiency comparison and analyzation have been performed among the nature-inspired optimization algorithms in that domain. Genetic Algorithm (GA) [197–199], Differential Evolution (DE) [200–209], Particle Swarm Optimization (PSO) [210, 221–227, 229–233, 236–240], Harmony Search (HS) algorithm [273], Bacterial Foraging (BF) algorithm [251] Ant Colony Optimization (ACO) [246–249], Artificial Bee colony (ABC) [256–260], Cuckoo Search (CS) [262–269], Firefly Algorithm (FA) [252–254], Bat Algorithm (BA)

[270, 271], are some nature inspired optimization algorithms which were effectively used in image enhancement and segmentation fields which are discussed in the next section.

5.1 Problem Formulation for Single objective Based Enhancement

In the case of nature inspired optimization algorithm based image enhancement, one parameterized transformation function is used to enhance the image. Suppose the transformation function (*T*) is associated with *K* number of parameters i.e. $P_1, P_2, \ldots, P_K$. The proper enhancement of the image crucial depends on the values of these parameters. The optimal values of the objective function have been found by maximizing/minimizing the objective function. Suppose output image (G) is found by applying *T* over input image *f*. Therefore mathematically it is expressed as:

$$G = T_{P_{1,P_{2,\ldots,P_{r,}}}}(f) \tag{4}$$

Objective function $fit(.)$. The optimal values of $P_1, P_2, \ldots, P_K$ are $P_{1O}, P_{2O}, \ldots, P_{KO}$ which have been completed by the following expression:

$$\{P_{1O}, P_{2O}, \ldots, P_{KO}\} = arg[max/min_{P_1,P_2,\ldots,P_K} \{fit(P_1, P_2, \ldots, P_K)\}] \tag{5}$$

where

$$LB_1 \leq P_1 \leq UB_1, LB_2 \leq P_2 \leq UB_2, \ldots, LB_i \leq P_i \leq UB_i, \ldots, LB_k \leq P_k \leq UB_k$$

and LB_i and UB_i are the lower and upper bound of the parameter P_i respectively.

5.2 Historical Developments in Nature-Inspired Optimization Algorithms for Image Enhancement

5.2.1 Evolutionary Algorithms in Image Enhancement

Genetic Algorithm (GA) which is a popular EA was successfully applied in image enhancement domain and GA based enhancement model proved its supremacy over existing image enhancement techniques such as Histogram Equalization (HE), Linear contrast stretching (LCS) etc. [28, 197, 198, 211–214]. Munteanu and Rosa [28] employed GA for tuning the parameters of one parameterized contrast stretching function with the help of one entropy and edge property based objective function. Experimental results showed that proposed GA based enhancement model gave better results than HE and LCS methods. In the same way, Archana et al. [212] proposed one better GA based image enhancement model which outperformed the model proposed by Munteanu [28]. In [197], GA based local contrast enhancement model was developed which was superior to HE. Hashemi et al. [213] proved the superior performance of GA based enhancement model by outperforming some well-known existing image enhancement techniques such as Gray-Level Grouping (GLG), Adaptive GLG (AGLG), HE and the method proposed by Saitoh [197]. Here, the author also used parameterized contrast stretching function with edge and entropy-based objective function nearly same as in [28, 212]. Pal et al. [214] proposed one GA based parameterized contrast stretching function where the combination of entropy, compactness, and index of area coverage had been used as an objective function which solely differed than the above discussed GA based enhancement models. Zhang and Wang [215] applied GA with wavelet neural network for enhancing the local as well as the global contrast of the image in wavelet domain. Later the same author proposed a GA based Adaptive typhoon cloud image enhancement in wavelet domain by considering entropy and Peak Signal to Noise Ratio (PSNR) as objective function [198]. GA was also applied for enhancing and denoising the colour images and produced natural enhanced colour images [213, 216–218]. For example, Lukac et al. [216] proposed one GA based weighted vector directional filter (WVDF) for denoising colour images which gave superior output than some standard filtering techniques. Shyu and leou [218] introduced six non-linear intensity mapping based colour image enhancement method with the assistance of GA and four quality parameters based objective function which are AC power measure, Compactness, Brenner's measures, and information noise change measure. In this method, at first RGB image was changed into LHS colour space, where L, H, and S stand for Luminance, Hue and Saturation component respectively. Then gray level transformation had been done over L component and the processed L component was again combined with unaltered H and S component to get the properly enhanced colour image. This type of enhancement is called hue preserving colour image enhancement method [218]. Experimental results proved that the proposed model is far better than existing colour image enhancement methods such as Uniform 3-D histogram specification, Individual 3-D histogram equalization and Individual 3-D LS equalization [218]. GA based image enhancement model was also proved its effective performance in medical imaging domain by enhancing the retinal images properly [219].

Another powerful EA called Differential Evolution (DE) was also proved its supreme performance in image enhancement domain by outperforming Particle Swarm Optimization (PSO) algorithm, HE and LCS based results [200, 202, 220]. In [202, 220], parameterized contrast stretching function had been used with the combination of edge and entropy as an objective function which is same as in [28, 212]. Bhandari et al. [201] and Suresh [205] employed DE for enhancing the colour satellite images properly and in both studies, DE outperformed PSO and several state of art methods in terms of the values of used objective functions and colour quality parameters such as Mean Square Error (MSE), PSNR, Structural-Similarity Index (SSIM), Feature Similarity Index (FSIM) etc. Oh and Hwang [204] proposed DE with a morphology-based homomorphic filter for enhancing several kinds of medical images like blood vessel images or vein images. DE was also modified to improve its performance in image enhancement domain.

5.2.2 Bio-inspired Algorithms in Image Enhancement

Particle Swarm Optimization (PSO) algorithm was broadly applied bio-inspired (SI based) algorithm over image enhancement domain and proved its exceptional performance [221–228]. Literature survey reports that most of the time PSO [223, 229–235] had been applied to set the parameters of one widely used image enhancement model which was same as in [28, 202, 212, 220]. The image enhancement model was consists of parameterized contrast stretching function with edge and entropy as the objective function and this PSO based model provided better results than HE, LCS and GA based image enhancement model [229–233, 236]. Shanmugavadivu et al. [222] proposed one HE variants with four enhancement control parameters which were properly set by PSO with the help of entropy as objective function. The proposed enhancement model outperformed the results of traditional HE, other standard modified HE variants and the method proposed by Kwok et al. [236]. In [224], PSO was successfully employed with a modified sigmoid function where the combination of edge and entropy considered as the objective function for contrast enhancement. The proposed model significantly outperformed HE, Adaptive HE (AHE) and GA based enhancement model proposed by Gorai [229]. PSO was fruitfully applied in discrete wavelet domain for the reduction of the noise [237]. Gorai and ghosh [238] employed their PSO based gray-level image enhancement model for enhancing the colour image with the help of HSI (Hue–Saturation–Intensity) colour space. The gray-level image enhancement model processed the Intensity (I) component and combined with unaltered H and S components to produce the final enhanced colour image. It was mathematically proved that proposed colour image enhancement model was purely hue preserving and gamut problem free and also outperformed the GA based results visually and mathematically [238]. In [239], PSO based gray level image enhancement model was also used for colour image through CIELAB colour space and outperformed some state of art methods such as HE, gamma correction etc. Hanmadlu et al. [240] proposed one fuzzy gray image enhancement model with the assistance of PSO which had been employed for colour images through the HSV colour space. In 2017, Sharma and Verma [241] also proposed one PSO based fuzzy image enhancement technique in discrete wavelet domain for enhancing colour satellite images. Mohan and Mahesh [242] proposed PSO based Contrast Limited Adaptive Histogram Equalization (CLAHE) based on Local Contrast Modification (LCM) method for enhancing the mammogram images properly and the proposed method gave superior performance to HE and traditional CLAHE based methods. Singh et al. [243] proposed PSO based piecewise gamma corrected histogram equalization method for the enhancement of colour standard as well as satellite images. Entropy and contrast had been used as objective function and image enhancement was formulated as maximization problem. Kanmani and Narsimhan developed PSO based gray level [244] and colour image enhancement model [245]. In both study, gamma correction with edge and entropy based objective function was employed for the proper enhancement of the images. Traditional LAB colour space is used for the enhancement of colour images [245].

Ant Colony Optimization (ACO) algorithm also proved its effective performance in gray and colour image enhancement field [246–249]. Verma et al. proposed one colour image enhancement model with the help of sigmoid transformation function, HSV colour space and fuzzy logic. ACO had been used to find the appropriate transformation function with the assistance of entropy as the objective function. The proposed colour image enhancement model significantly outperformed the well-known Bacterial Foraging (BF) based model proposed by Hanmadlu et al. [250]. ACO based colour image filtering method also proved its efficiency where Minimum Absolute Error (MAE) and Minimum Square Error (MSE) had been used as objective function [248].

Bacterial Foraging (BF) algorithm was proved its supreme performance over colour image enhancement field [250, 251]. Hanmandlu et al. [250] and Verma et al. [251] applied BF algorithm and adaptive BF algorithm in HSV colour space respectively for improving the quality of the colour images and experimental results showed they outperformed HE, GA [250] and visual factor approaches based outputs.

Firefly Algorithm (FA) [252–254] is a new kind of Bio-inspired (SI based) algorithm have showed its effective performance in image enhancement field by giving better results than HE, LCS, GA and PSO [252, 254]. FA based image enhancement model also outperformed another newly invented swarm based algorithm called Cuckoo

Search (CS) in terms of used objective function maximization ability [253]. Dhal and Das developed one FA based colour retinal fundus image enhancement model where FA was employed to set the control parameters of the used weighted and thresholded HE variant and Contrast Limited Adaptive HE (CLAHE) with the help of Peak-Signal to Noise Ratio (PSNR) as objective function [295]. Experimental results showed that proposed colour retinal image enhancement model provided superior results than some well-existing techniques.

Artificial Bee Colony (ABC) algorithm was employed by several authors for enhancing the gray-level images [255–258] as well as for colour images [257, 259, 260]. In [255], ABC algorithm was used to tune the parameters of a contrast stretching function with the help of edge and entropy-based objective function same as in [28, 202, 203, 212] and gave better results than GA and PSO. Benala et al. [258] proposed one ABC algorithm based hybrid filtering method for image enhancement purpose which clearly outperformed GA based hybrid filtering technique and several state of art filtering methods namely Mean Filter, Median Filter, Mode Filter, Cone Filter and so on. Draa and Bouaziz [257] extended the gray level enhancement technique to colour image by enhancing the R, G and B component individually where each component had been taken as gray level image. Then three enhanced components were integrated to compute the final enhanced colour image. Experimental results showed that ABC gave better results than CS visually and mathematically for the gray-level image as well as for colour images. Bhandari et al. [259] employed ABC algorithm in discrete wavelet domain for enhancing the colour satellite images and proved its superior performance to PSO based methods. In 2017, Chen et al. [260] proposed one ABC based gray and colour image enhancement model where a new objective function had been formulated with the combination of edge information, entropy and contrast measure. The proposed ABC based model outperformed some popular NIOAs based enhancement models such as GA based model proposed by Hashemi et al. [213], PSO based model proposed by Gao et al. [232], CS-based model proposed by Agrawal [261], ABC based models proposed by Draa [257] and Joshi [256].

Cuckoo Search (CS) is simple NIOA but proves its effective performance over image enhancement field by tuning the parameters of some non-linear transformations functions with the help of diverse objective functions in spatial as well as in wavelet domain [262–266]. CS with parameterized contrast stretching method with edge and entropy as objective function had been used for gray level image enhancement and outperformed HE, LCS and PSO base outputs [261, 265]. Babu and Sunitha [264] developed morphology and CS based gray image enhancement model where CS gave better results than GA, PSO and ABC in terms of the values of used objective function. In the field of colour image enhancement, CS-based enhancement model was proposed by Saini and Narang in HSV colour space and CS gave better results than BF and ACO in terms of quality parameters and computational time [262]. Biswas et al. [267] used a multi-scale retinex algorithm with CS algorithm for the enhancement of colour microscopic images and CS was superior to PSO and ABC in this field. Ashour et al. [268] proposed one log transform based computed tomography image enhancement where CS was applied with edge and entropy-based as the objective function to set the enhancement control parameters of the log transform and here also produced better results than PSO based model. CS was also applied in wavelet domain [266, 269] for enhancing the colour satellite image [266] and medical images such as MRI, mammogram images [269] where CS based model outperformed HE, CLAHE and Discrete Cosine Transform (DCT) based enhancement models [266, 269].

Newly invented Bat Algorithm (BA) also applied for optimizing the enhancement control parameters of one HE variants with the help of entropy as objective function [270]. Proposed enhancement model gave superior performance to the several variants of traditional HE. BA also employed for enhancing the fingerprint images properly with the help of gray level mapping function and edge and entropy-based objective function [271]. Dhal et al. [291, 292] proposed BA based image enhancement model based on the parameterized contrast stretching function with entropy and edge information as objective function. In these papers, BA gave superior results to CS [291] and FA [292] in terms of maximization of the objective function and other quality parameters.

A new gray level image enhancement technique was proposed by Zeng and Wang [272] with help of Shuffled Frog Leaping Algorithm (SFLA). Here author used an improve version of SFLA.

5.2.3 Physics and Chemistry Based Algorithms in Image Enhancement

Literature review of the application of physics/chemistry algorithms over image enhancement is not so rich because Sect. 2 shows that the most of these algorithms are newly developed and also an emerging class of NIOAs which has attracted researchers. Harmony search (HS) algorithm which is well-known physics/chemistry algorithm was used for gray level image enhancement with the assistance of parameterized contrast stretching function and edge and entropy-based objective function. HS based enhancement model outperformed traditional HE and contrast stretching methods [273, 274].

Zhang et al. [275] proposed one Simulated Annealing (SA) algorithm based image enhancement model with the help of wavelet neural network (WNN). In that paper, Incomplete Beta Transform (IBT) was employed to produce non-linear gray transform curve. Optimal transform parameters were obtained by SA and WNN within reasonable computational time.

Zhao also employed Gravitational Search Algorithm (GSA) to find the optimal parameters of IBT in [276]. GSA also hybridized with PSO and improved the performance of PSO in terms of capability of producing better enhanced images [277].

Yaghoobi et al. [278] proposed Black Hole algorithm (BH) for gray level image enhancement. The performance of proposed method was tested with some well known enhancement techniques viz. PSO,GA, and CS. Kaushal et al. [279] employed Water cycle algorithm (WCA) for colour image enhancement based multi-objective contrast enhancement approach.

5.2.4 Other Algorithms in Image Enhancement

Algorithms belong to 'other' class are also mostly newly invented and also an emerging class of NIOAs. The recent development growth rate of this class is greater than other three classes according to the Sect. 2. Ye et al. [280] employed Differential Search Algorithm (DSA) and Backtracking Search Algorithm (BSA) for enhancing the gray level image enhancement with the assistance of entropy and histogram's variance based objective function. DSA outperformed BSA, HE and Liner Contrast Stretching (LCS) in terms of the values of the objective function. Gan and Duan proposed one chaotic Differential Search (CDS) algorithm with lateral inhibition (LI) mechanism for biological image processing such as enhancement and edge extraction. Proposed CDS with LI gave superior results than CDS, classical DSA and PSO [281]. Simple League Championship Algorithm (LCA) [282] was used to find the optimal parameters of the popular parameterized contrast stretching function with the help of edge and entropy-based objective function. The output images of the proposed enhancement model were associated with greater contrast than the original one [LCA].

Therefore, the above literature review clearly reveals that NIOAs are used rapidly in image enhancement domain. But most of the newly invented algorithms are do not applied in image enhancement field such as algorithms belong to bio-inspired (not SI), physics/chemistry and 'other' class. GA, DE, PSO, CS, ABC, ACO are widely employed optimization algorithms in this domain. According to literature report, EA and bio-inspired (not SI) based algorithms are the major applied classes. Therefore, it is challenging task to analyze the rest other algorithms in that field.

5.3 Improvement of Nature-Inspired Optimization Algorithms in Image Enhancement Domain

Improvement of the EAs is also performed in image enhancement field for their better performance. For example, to improve the efficiency of GA in image enhancement field, it was also hybridized with Differential Evolution (DE) and hybrid GA gave better results in terms of objective function maximization/minimization ability [283]. Mutation factor and crossover rate had been modified by chaotic sequence [202] or Beta distribution [201] of traditional DE algorithm and experimental result showed that modified DE was far better than traditional DE and other optimization algorithms such as PSO and Artificial Bee Colony (ABC) algorithms in image enhancement field with faster convergence rate, better values of objective function, quality parameters and also maintained a good diversity property [201, 202]. In [205], hybridization of DE with Cuckoo Search (CS) algorithm had been performed to improve the performance of DE, where DE was used for exploration and CS for exploitation. Experimental results proved that hybrid DE-CS gave better results than state of art enhancement algorithms, PSO, PSO-CS, DE-SA, and modified DE proposed by Bhandari et al. [201]. Mutation factor and crossover rate had been modified by chaotic sequence of traditional DE algorithm and experimental result showed that modified DE was far better than traditional DE in image enhancement field with faster convergence rate and also maintained a good diversity property [202]. Lévy Flight with chaotic step length had been used to generate new solutions and one population diversity measurement technique had been used as a safe guard from premature convergence in [294, 299, 301] to modify FA [301], ABC [299] and DE [294] respectively, which outperformed the traditional FA, ABC and DE in the image enhancement domain by maximizing the employed objective function with faster convergence rate. One logistic equation based modified chaotic DE based colour image enhancement model was also developed by Dhal et al. [296] where combination of Fractal dimension (FD) and Quality Index based on Local Variance (QILV) considered as objective function. Fuzzy contrast stretching function was employed through the Exact HSI (eHSI) [26] model for the enhancement of colour image. The modified DE gave superior results to traditional DE, PSO and GA. Whereas, the proposed *colour* image enhancement model produced better results than well-known Automatic Colour Equalization (ACE) [284] algorithm.

Literature reports some modified and improved variants of bio-inspired algorithms. For example, PSO was also hybridized with other NIOAs such as CS [280], Gravitational Search Algorithm (GSA) [277], and Artificial Immune System (AIS) algorithm [285] for the improvement of performance in image enhancement domain. Mahapatra et al. [285] hybridized PSO with AIS algorithm and gave superior performance to traditional PSO, HE and LCS based results in terms of image quality parameters and used objective function. Ye et al. [280] combined CS and PSO for the betterment of exploration and exploitation capability and experimental results proved that this hybrid algorithm gave better results than several well-known optimization algorithms such as traditional PSO, CS, GA, Differential Search Algorithm (DSA) etc. Sharma and Kapur [277] hybridized PSO with newly invented GSA algorithm and the hybrid variant had the better capability than traditional PSO in terms of the values of image quality parameters.

Pan [249] increased the efficiency of traditional ACO algorithm by hybridized with GA and the proposed ACO-GA algorithm gave superior performance to GA and ACO algorithms in terms of the maximization ability of employed objective function. Hoseini and Shayesteh [247] developed one hybrid ACO algorithm based gray level image enhancement model which gave better results than HE and LCS methods. GA and SA were incorporated to build the hybrid ACO algorithm which was used to optimize the parameters of one non-linear transformation function with the assistance of the combination of Standard deviation, edge information and entropy as objective function [249].

Recently, Mondal et al. [286] modified the ABC algorithm by incorporating the crossover operation of GA into it and experimental revealed that ABC based model gave better performance than some well-known HE variants visually and quantitatively. Joshi and Prakash [256] proposed one modified ABC with directional constraints and produced better results than GA and traditional ABC. One logistic equation based chaotic ABC algorithm had been employed to develop one Multi-thresholded Histogram Equalization (HE) variant where chaotic DE was used to perform the multi-thresholding of the considered image's histogram [287]. The HE variant successfully employed in histopathology image enhancement field and provided well enhanced images. Logistic equation based chaotic sequence was used because it generates population of random number with greater variance [299, 300].

Draa et al. [288] proposed one improved variant of FA with the help of Opposition-based Learning (OBL) called Opposition-based FA (OFFA) efficiently employed in MRI image enhancement and denoising domain. Experimental results proved that OFFA gave superior performance to the traditional FA and HE in terms of the employed edge and entropy-based objective function [28, 202, 203, 212] and other used quality metrics.

Suresh et al. [289] modified CS in satellite image enhancement domain with the help of chaotic initialization phase, adaptive Levy flight strategy and mutative randomization phase. The proposed CS algorithm gave superior performance to traditional CS, PSO, DE, FA, Beta DE (BDE) [201] in terms of the values of used edge and entropy-based objective function and other image quality parameters [289]. Performance improvement of traditional CS was done by incorporating communication between solutions, different search strategies, and different adaptive mutation strategies [297, 300]. Search strategies greatly helped to improve the efficiency of the CS in [297] and outperformed PSO and several existing modified variants of CS in image enhancement field by considering four objective functions. Here, Combination of Fractal dimension (FD) and Quality Index based on Local Variance (QILV) based one objective was proposed which outperformed three well-known objective functions namely Combination of edge information and entropy [229], Shannon Entropy [222], Combination of contrast, energy, and entropy [298, 301] mathematically in brightness preservation image enhancement field. Same author also applied one modified CS for the enhancement of mammogram images with the assistance of well recognized weighted and thresholded HE variants and CLAHE, where also Combination of Fractal dimension (FD) and Quality Index based on Local Variance (QILV) opted as objective function [290]. Experimental results showed that proposed HE variants based enhancement model gave well enhanced outputs and the employed objective function carried out a significant role in mammogram image enhancement field.

Recently, Dhal and Das [293, 298] developed modified BA variants in image enhancement field with the help of proposed dynamic inertia weight [298], self-adaptive parameter strategy [293, 298], and local search strategies [293]. The modification of the proposed dynamic inertia weight and parameter updation rules of every individual had been done depending on the performance of the considered solution [298]. Therefore, the proposed inertia weight was completely different than random inertia weight. Incorporating of both inertia weight and self-adaptive parameter strategy significantly improved the efficiency of the BA and it gave superior results to the five efficient existing BA variants and PSO. The proposed BA successfully employed to tune the four parameters of one parameterized weighted and thresholded HE variants with the assistance of the combination of contrast, energy, and entropy as objective function. The proposed modified HE variant based enhancement model provided better results than some popular existing HE variants visually and mathematically. The same authors [293] presented another three improved BA variants by incorporating previously developed self-adaptive parameter strategy and three efficient local search strategies. Three local search strategies were developed with the help of chaotic sequence, k-neighbourhood concept, and center of mass of the population to replace the uniform distribution based local search in classical BA. The proposed self-adaptive strategy for the BA's parameters adjustment plays a crucial role by outperforming three well existing parameter adaption techniques. Finally the proposed three BA variants were tested over five recognized parameterized image enhancement models and gave superior results than five popular BA variants.

5.4 Objective Functions for Image Enhancement

Objective functions are also carried out a great role in image enhancement fields. Several objective functions are proposed in literature are listed in Table 3. Finding new objective function or finding the best objective function for different kinds of images is also a great challenge.

5.5 Enhancement Quality Parameters

Quantitative performance measurements are significant to compare among the different image enhancements techniques for gray level as well as for colour images. The well-known quality measurement metrics for gray level and colour images have been discussed below.

5.5.1 Gray Level Quality Parameters

There are several gray level image quality measurement parameters exist in literature. Among them 12 well-known parameters are given in Table 4. Quality of an enhanced image is judged depending on the higher or lower values of the considered parameter. It is reported in literature that a single quality parameter measurement does not satisfy the requirements or not signify the better quality image in terms of visual perception [5, 293, 297, 300]. Therefore it is intelligent way to analyze the quality of an enhanced image by computing the values of more than one quality parameters. Sometimes selection of quality parameters depends on the image type on which the enhancement has been performed. For example, it is reported in [295] that entropy is not a good criterion to judge the quality of the enhanced retinal fundus image. Whereas, this entropy measurements had proved its effective performance in standard gray level image enhancement domain. Based on the presence of original image the image quality parameters could be classsified into two categories: (a) Referenced Quality parameters, (b) Non-Referenced Quality parameters. In Referenced Quality parameter measurement, only the presence of the enhanced image is sufficient. Whereas, in referenced quality measurement parameters use the original image as the reference and compute the similarity between the original and enhanced images [310]. The image quality parameters for gray level and colour images and their properties are given in Tables 4 and 5 respectively.

5.5.2 Colour Quality Parameters

Any gray level quality parameter can be easily applied for measuring the quality of the colour image by employing over the different channels of the considered colour image. After that computes the average of the quality parameter to judge the overall quality of the colour image. But, simple popular parameters for gray level image enhancement cannot be used in colour image domain as each colour model has their own representation for the brightness component [19]. Therefore, when we compare among the results of different colour model based enhanced images, computing the average of used gray level quality parameter is not well suited. In literature, some referenced and non-referenced colour quality parameters are exists to overcome that problem. Two popular non-referenced quality assessment parameters are Cube Root Mean Enhancement (CRME) [310, 311], and Colour Quality Enhancement (CQE) [310, 311]. Whereas, two referenced quality assessment parameters are Modified Peak Signal to Noise Ratio ($PSNR_Q$) [312], and PSNR-HVS-M [313]. The explanation of these metrics is as follows:

(a) *Cube Root Mean Enhancement (CRME)*

CRME is a contrast measurement technique for colour image which measures the contrast not only within each colour plane but also across the colour planes [310, 311]. CRME computes the contrast by measuring the relative difference of colour cube center and all the neighbours in that cube. It is also correlated with HVS property. So, the greater value of CRME represents greater contrast with natural enhancement [310, 311].

(b) *Colour Quality Enhancement (CQE)*

CQE is the linear combination of the chrominance information i.e. colourfulness with sharpness and contrast [310, 311]. This metric also has the greater correlation with human visual perception. Therefore, a large value of CQE signifies the better quality of the image.

(c) $PSNR_Q$

This metric is developed based on the linear combination of pixel value distortion, structural distortion, and edge distortion measurements [312]. It is proved that $PSNR_Q$ is

Table 3 Lists of existing objective functions in literature for image enhancement

Objective function	References
Combination of edge information and entropy	[28, 197, 200, 202, 212, 213, 223, 224, 229–233, 238, 244, 245, 252, 255, 257, 261, 263, 265, 268, 271, 273, 274, 280, 285, 288, 289, 291–294]
Entropy, compactness and index of area coverage	[214]
AC power measure, Compactness, Brenner's measures, and information noise change measure	[218]
Peak Signal to Noise Ratio (PSNR)	[219, 295]
Shannon Entropy	[201, 222, 246, 270, 293]
Entropy, standard deviation and edge	[205]
Contrast based quality estimation (CQE)	[256]
edge information, entropy and contrast measure	[260]
Standard deviation, edge and entropy	[247]
Combination of Shannon Entropy and Fuzzy entropy	[251]
Entropy and the visual factors	[250, 262]
Fuzzy contrast	[240]
Fuzzy entropy	[241]
Entropy, histogram flatness and histogram spread	[277]
Combination of Fractal dimension (FD) and Quality Index based on Local Variance (QILV)	[290, 293, 296, 297]
Combination of contrast, energy, and entropy	[293, 298–301]

more efficient and more correlated with HVS compared to traditional PSNR.

(d) *PSNR-HVS-M*

This metric is developed by considering the DCT basis function [313]. PSNR-HVS-M has been used to evaluate the quality as it represents two significant features of HVS. First, it reveals the fact that sensitivity to distortions in low spatial frequencies is larger than to distortions in high spatial frequencies. Second, masking effect (the worse ability of human vision to notice distortions in heterogeneous and textural image areas) has been taken into consideration. The greater value represents the better quality.

6 Multi-objective Based Image Enhancement

6.1 Problem Formulation for Multi-objective Based Enhancement

The image enhancement problem can be formulated as a multi-objective problem by simultaneously minimizing/maximizing M objective functions represented by the following expression:

$$\{P_{1O}, P_{2O}, \ldots, P_{KO}\} = arg[max/min_{S_K}\{Fit_1(S_K), Fit_2(S_K), \ldots, Fit_M(S_K)\}] \quad (6)$$

where $S_k = \{P_1, P_2, \ldots, P_K\}$.

6.2 Historical Developments in Multi-objective Nature Inspired Optimization Algorithms Based Image Enhancement

Literature and from the above discussion prove that a single quality measurement metric/objective criterion is not sufficient to judge an enhanced image obtained by some method [27]. Therefore, researchers formulated the image enhancement as multiobjective optimization problem where more than one objective criterion simultaneously assesses the enhanced images. Bhandari et al. [27] developed one nondominated sorting GA-II (NSGA-II) algorithm based multi-objective gray-level image enhancement model by using three objective functions which are Entropy, Compactness and index of area coverage. The enhanced images with medium entropy, and low compactness and IOAC measures were found better among the several enhanced images obtained by Pareto front using NSGA-II. The proposed model gave superior results than the single objective base classical GA where the product of entropy, compactness and IOAC had been considered as

Table 4 Quality parameter for gray level image

Sl. no.	Quality parameter	Desired value	References
1.	Quality Index based on Local Variance (QILV)	Higher	[293, 297, 302]
2.	Absolute Mean-Brightness Error (AMBE)	Lower	[19]
3.	Mean Square Error (MSE)	Lower	[5, 295, 300]
4.	Peak signal-to-noise ratio (PSNR)	Higher	[5, 295, 300]
5.	Normalized Cross-Correlation (NK)	Higher	[303]
6.	Structural Content (SC)	Higher	[303]
7.	Universal Image Quality Index (UIQI)	Higher	[304]
8.	Structural Similarity Index (SSIM)	Higher	[304–306]
9.	Feature Similarity Index (FSIM)	Higher	[307]
10.	Gradient magnitude similarity deviation (GMSD)	Lower	[308]
11.	Contrast	Higher	[23, 256, 301, 309]
12.	Entropy	Higher	[5, 6, 290, 300]

Table 5 Quality parameter for colour image

Sl. no.	Quality parameter	Desired Value	References
1.	Cube Root Mean Enhancement (CRME)	Higher	[25, 296, 310, 311]
2.	Colour Quality Enhancement (CQE)	Higher	[25, 296, 310, 311]
3.	$\mathrm{PSNR_Q}$	Higher	[25, 296, 312]
4.	PSNR-HVS-M	Higher	[25, 296, 313]

objective function. Kwok et al. [236, 314] proposed PSO based multiobjective gray-level image enhancement model by considering gamma correction as image enhancement method and contrast and mean intensity of the image as objective functions. There is always a trade off between the preservation of the mean intensity and the contrast of an image. This paper formulated this problem as bi-objective problem and solved using PSO. Later, the same author employed multi-objective PSO in colour correction based colour image enhancement field by taking into account the removal of illumination colour cast and the maximal recovery of information contained in the image [236]. Peng et al. [315] proposed SR noise-based mammogram image enhancement model by using structural similarity (SSIM) index and contrast sensitivity information as objective criterion. The proposed SR noise-based model gave better results than classical Contrast Limited Adaptive Histogram Equalization (CLAHE) method.

7 Graphical Analysis of the Nature-Inspired Optimization Algorithm Based Image Enhancement

Graphical analysis has also been done based on the application of NIOAs over image enhancement domain. Three factors have been considered in graphical analysis: (a) Year wise development of NIOA based image enhancement models which show the popularity of this research area. Figure 5 represents the year wise development statistics and clearly demonstrates that in the recent years the applicability of NIOAs for solving the image enhancement problems is rapidly increasing. (b) Application areas of NIOAs based images enhancement models depending on image type is represented by Fig. 6. It can be seen from Fig. 6 that most of the applications have been done over standard gray and colour images. Only a little percentage of models has been considered the medical image and satellite image. Therefore, in future, most application should be performed over these medical and satellite based image enhancement domain. (c) Fig. 7 which demonstrates the class wise application of the NIOAs clearly reveals that Bio-inspired based NIOAs are mostly applied in this novel domain. The class wise popularity of NIOAs over image enhancement domain can be easily verified from the following statistics: Bio-inspired (68%) > EA (23%) > Physics and chemistry based (6%) > Other class (3%). Therefore, it is a great challenging task to apply the rest other algorithms in image enhancement domain to prove their efficiency.

8 Application Areas of Nature-Inspired Optimization Algorithms Based Image Enhancement Models

NIOA based image enhancement models are widely used in the different field such as medical imaging, satellite imaging, historical document imaging, and so on. The application of NIOA based image enhancement models over medical image, satellite image are given in Table 6. Literature shows that NIOA based enhancement model prove its effective performance over different medical image fields such as MRI, Retinal fundus, mammogram, histopathology image and over satellite image enhancement field.

9 Conclusion and Future Research Issues

From the above discussion, it can be easily concluded that this NIOA based image enhancement field is quite young and emerging with new concepts and applications. There are several future research directions which should be investigated. The futures directions are divided into categories include:

9.1 Future Directions in Image Enhancement Field

Future directions of this field are mentioned as follows:

(a) It can be seen throughout the paper that incorporating of parameters into the simple image enhancement techniques make it superior and adaptive to several kinds of images. Here, simple contrast stretching function and traditional Histogram Equalization method has been modified by incorporating parameters into them and the experimental results prove the superiority over classical contrast stretching function and HE. Therefore in future other simple image enhancement techniques could be modified into parameterized variants and applied to different image enhancement domains.

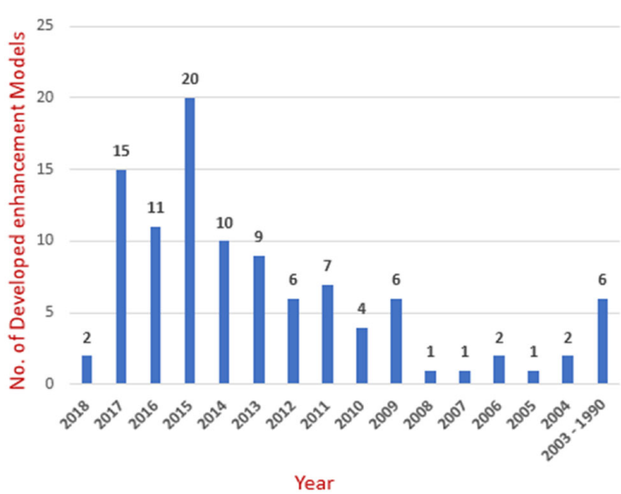

Fig. 5 Year wise development of NIOA based image enhancement models

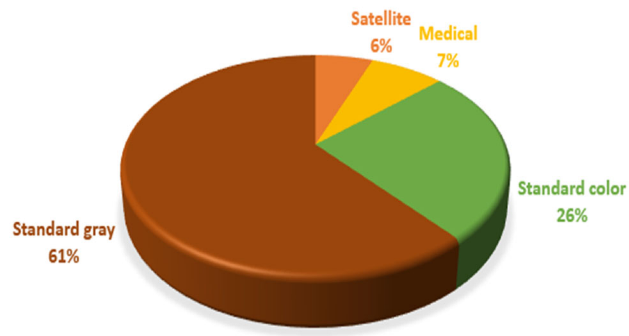

Fig. 6 Application of NIOA based image enhancement model over different image type

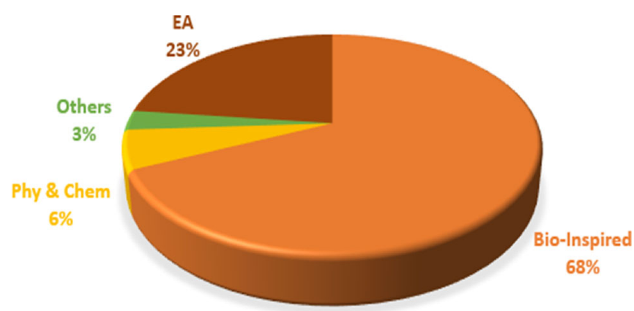

Fig. 7 Class wise application of NIOA in image enhancement domain

(b) But the proper enhancement of different kinds of images crucially depends on the appropriate tuning of the associated parameters and the employed objective functions. Therefore the development of new objective functions which will facilitate the proper requirement is a great challenge in future. On the other hand, application and efficiency measurement of other NIOAs over several kinds of image enhancement fields will also be an interesting work because the superiority of any NIOA purely depends on the considered problem type on which it is applied.

(c) There is no unique measure to quantitatively judge the quality of a given image enhancement operator or transformation function. It is also not clear which measure is to be used for a specific type of images. Therefore, multi-objective image enhancement model can be developed where multiple objective functions are simultaneously taken into consideration during enhancement. Although the literature of the multi-objective based image enhancement is not so rich but it is proved that formulation of image enhancement as multi-objective provides superior results than single objective based model.

(d) Development of NIOA based image enhancement models for satellite and medical image is a demanding research area in recent era. But it is verified from

Table 6 Real life application of NIOAs based enhancement

Medical image	CS—Biswas et al. [267], Daniel and Anitha [269], Dhal et al. [290]
	GA—Daniel and Anitha [219]
	DE—Oh and Hwang [204]
	ABC—Dhal et al. [287]
	FA—Dhal et al. [295], Draa et al. [288]
	PSO—Mohan and Mahesh [242]
Satellite image	ABC—Bhandari et al. [259]
	CS—Bhandari et al. [266], Suresh et al. [289]
	DE—Bhandari et al. [201], Dhal et al. [294]
	GA—Quraishi et al. [316]

the above discussion that a little percentage of work has been done in this area. Therefore, in future, more concentration should be given in this area.

(e) Colour image processing always one tough but well-needed task. Hue preserving and gamut problem free colour image enhancement are the main necessity of this field. But, enhancement through traditional colour space is hue preserving but not gamut problem free. Thus modified colour models should develop which are hue preserving, gamut problem free and any gray level image enhancement technique successfully employed through these modified colour models.

9.2 Future Directions of Nature-Inspired Optimization Algorithms

Applications and the improvements of Nature-inspired optimization algorithms is the key part of this review paper. Several interesting future research agenda that can be enumerated from this part are as follows.

(a) At first few NIOAs are employed in the literature. Therefore it is a great challenging task to employ other NIOAs in image enhancement and segmentation fields to measure their efficiency because the effectiveness of the NIOAs is purely problem oriented.

(b) From the Sect. 2, it is quite possible to develop new effective NIOAs. The analysis of NIOAs are performed is usually qualitative. Therefore, more insights could be gained by looking at algorithms mathematically. There are many ways of analyzing NIOAs with mathematically, but these analyses could have rigorous assumptions which can be also impractical in some cases. Currently different well-known ways of mathematical analysis are dynamic systems, fixed-point theory, Markov chain theory, self-organization, filtering and so on. But in future, development of proper mathematical framework could open a fresh research domain.

(c) Several improvement strategies such as parameters adaptivity, inertia weight, global and local search strategies are formulated and applied over different NIOAs. The improvement strategies are significantly successful to improve the efficiency of several NIOAs in image enhancement and segmentation domain. In future, the existing improvement strategies can be incorporated into other NIOAs. On the other hand new novel improvement strategies could be developed by considering the different structural shortcomings of the considered NIOAs.

(d) In this paper, NIOAs are applied over only image enhancement. In future, NIOAs could be applied over other major components such as image segmentation, compression, restoration, registration, feature selection etc.

(e) Not only digital image processing field, the classical and developed improved NIOAs can be employed in different fields of engineering such as civil engineering, mechanical engineering, electrical-electronics engineering, medical and bio-medical engineering etc.

(f) Multi-objective optimization can be a great future direction in any NIOAs based application field because any real time optimization problem always considers more than one objective. It is also interesting to prove that if one NIOA is very efficient to maximize/minimize one objective function it does not mean that it is also very useful in multi-objective based optimization domain.

Funding This study was funded under DST-PURSE scheme.

Compliance with Ethical Standards

Conflict of interest Krishna Gopal Dhal has received research Grants from PURSE Scheme, DST, India. Swarnaji Ray, Arunita Das, Sanjoy Das declare that thay have no conflict of interest.

References

1. Gonzalez RC, Woods RE (2002) Digital image processing, 2nd edn. Prentice Hall, New York
2. Agaian SS, Panetta K, Grigoryan AM (2001) Transform-based image enhancement algorithms with performance measure. IEEE Trans Image Process 10(3):367
3. Zhong S, Jiang X, Wei J, Wei Z (2013) Image enhancement based on wavelet transformation and pseudo-colour coding with phase-modulated image density processing. Infrared Phys Technol 58:56–63
4. Starck JL, Murtagh F, Candès EJ, Donoho DL (2003) Gray and colour image contrast enhancement by the curvelet transform. IEEE Trans Image Process 12(6):706–717
5. Dhal KG, Das S (2017) Combination of histogram segmentation and modification to preserve the original brightness of the images. Pattern Recognit Image Analy 27(2):200–212
6. Dhal KG, Sen S, Sarkar K, Das S (2016) Entropy based range optimized brightness preserved histogram-equalization for image contrast enhancement. Int J Comput Vis Image Process 6(1):59–72
7. Iwasokun GB, Oluwole CA (2014) Image enhancement methods: a review. Br J Math Comput Sci 4(16):2251–2277
8. Starck JL, Candès EJ, Donoho DL (2002) The curvelet transform for image denoising. IEEE Trans Image Process 11(6):670
9. Thriveni R (2013) Satellite image enhancement using discrete wavelet transform and threshold decomposition driven morphological filter. In: 2013 international conference on computer communication and informatics (ICCCI), Jan 2013. IEEE, pp 1–4
10. Naik SK, Murthy CA (2003) Hue preserving colour image enhancement without gamut problem. IEEE Trans Image Process 12:1591–1598
11. Strickland RN, Kim CS, McDonnel WF (1987) Digital colour image enhancement based on saturation component. Opt Eng 26:609–616
12. Thomas BA, Strickland RN, Rodriguez JJ (1997) Colour image enhancement using spatially adaptive saturation feedback. In: Proceedings of IEEE international conference on image processing
13. Pitas I, Kinikilis P (1996) Multichannel techniques in colour image enhancement and modelling. IEEE Trans Image Process 5:168–171
14. Weeks AR, Hague GE, Myler HR (1995) Histogram specification of 24-bit colour images in the colour difference (C–Y) colour space. J Electron Img 4:15–22
15. Trahanias PE, Venetsanopoulos AN (2001) Colour image enhancement through 3-D histogram equalization. In: Proceedings of 15th IAPR international conference on image processing, pp 1077–1080
16. Han JH, Yang S, Lee BU (2011) A novel 3-D colour histogram equalization method with uniform 1-D gray scale histogram. IEEE Trans Image Process 20:506–512
17. Mlsna PA, Rogriguez JJ (1995) A multivariate contrast enhancement technique for multispectral images. IEEE Trans Geosci Remote Sens 33:212–216
18. Mlsna PA, Zhang Q, Rogriguez JJ (1996) A recursive technique for 3-D histogram modification of colour images. In: Proceedings of IEEE international conference on image processing, vol III, pp 1015–1018
19. Kong NSP, Ibrahim H (2008) Colour image enhancement using brightness preserving dynamic histogram equalization. IEEE Trans Consum Electron 54:1962–1968
20. Bockstein IM (1986) Colour equalization method and its application to colour image processing. J Opt Soc Am 3:735–737
21. Shyu MS, Leou JJ (1998) A genetic algorithm approach to colour image enhancement. Pattern Recognit 3:871–880
22. Yang CC, Rodriguez JJ (1995) Efficient luminance and saturation processing techniques for bypassing colour coordinate transformation. In: Proceedings of IEEE conference on systems, man and cybernetics, vol 1, pp 667–672
23. Raju G, Nair MS (2014) A fast and efficient colour image enhancement method based on fuzzy-logic and histogram. Int J Electron Commun 68:237–243
24. Gorai A, Ghosh A (2011) Hue preserving colour image enhancement by particle swarm optimization. In: In Proceedings of the IEEE recent advances in intelligent computational systems (RAICS). IEEE, pp 563–568
25. Dhal KG, Das S (2018) Hue preserving colour image enhancement models in RGB colour space without gamut problem. Int J Signal Imaging Syst Eng 11:102
26. Chien CL, Tseng DC (2011) Colour image enhancement with exact HSI colour model. Int J Innov Comput Inf Control 7:6691–6710
27. Bhandari D, Murthy CA, Pal SK (2009) Image enhancement using multi-objective genetic algorithms. In: PReMI, pp 309–314, Dec 2009
28. Munteanu C, Rosa A (2000) Towards automatic image enhancement using genetic algorithms. In: Proceedings of the 2000 Congress on Evolutionary Computation, vol 2. IEEE, pp 1535–1542
29. Jain AK (1989) Fundamentals of digital image processing. Prentice-Hall, Englewood Cliffs
30. Ekstrom MP (2012) Digital image processing techniques, vol 2. Academic Press, London
31. Kundu MK, Pal SK (1990) Automatic selection of object enhancement operator with quantitative justification based on fuzzy set theoretic measures. Pattern Recognit Lett 11(12):811–829
32. Fister I Jr, Yang XS, Fister I, Brest J, Fister D (2013) A brief review of nature-inspired algorithms for optimization. arXiv preprint arXiv:1307.4186
33. Kulkarni AJ, Krishnasamy G, Abraham A (2017) Cohort intelligence: a socio-inspired optimization method. Springer, Heidelberg. https://doi.org/10.1007/978-3-319-44254-9_1
34. Yang XS (2018) Mathematical analysis of nature-inspired algorithms. In: Yang XS (ed) Nature-inspired algorithms and applied optimization. Springer, Cham, pp 1–25
35. Yang XS (2010) Nature-inspired metaheuristic algorithms. Luniver Press, Bristol
36. Nanda SJ, Panda G (2014) A survey on nature inspired metaheuristic algorithms for partitional clustering. Swarm Evol Comput 16:1–18
37. Brownlee J (2011) Clever algorithms: nature-inspired programming recipes. Jason Brownlee
38. Fister I Jr (2013) A comprehensive review of bat algorithms and their hybridization. Masters thesis, University of Maribor, Slovenia

39. Garey M, Johnson D (1979) Computers and intractability: a guide to the theory of NP completeness. W.H. Freeman, New York
40. Darwin C (1859) On the origin of species. Reprinted by Harvard University Press, Cambridge (1964)
41. Yang XS (2012) Flower pollination algorithm for global optimization. In: International conference on unconventional computing and natural computation. Springer, Berlin, pp 240–249, Sept 2012
42. Fister I Jr, Mlakar U, Brest J, Fister I (2016) A new population-based nature-inspired algorithm every month: is the current era coming to the end. In: StuCoSReC: proceedings of the 2016 3rd student computer science research conference. University of Primorskapp, Koper, pp 33–37
43. Yang XS, Cui Z, Xiao R, Gandomi AH, Karamanoglu M (eds) (2013) Swarm intelligence and bio-inspired computation: theory and applications. Newnes. Elsevier, Amsterdam
44. Wolpert DH, Macready WG (1997) No free lunch theorems for optimization. IEEE Trans Evol Comput 1(1):67–82
45. Fister I, Yang XS, Ljubič K, Fister D, Brest J (2014) Towards the novel reasoning among particles in PSO by the use of RDF and SPARQL. Sci World J. https://doi.org/10.1155/2014/121782
46. Colorni A, Dorigo M, Maniezzo V (1992) Distributed optimization by ant colonies. In: Toward a practice of autonomous systems: proceedings of the first European conference on artificial life. MIT Press, p 134
47. Mirjalili S (2015) The ant lion optimizer. Adv Eng Softw 83:80–98
48. Karaboga D, Basturk B (2007) A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. J Glob Optim 39(3):459–471
49. Rosenberg LB (2015) Human swarming, a real-time method for parallel distributed intelligence. In: 2015 swarm/human blended intelligence workshop (SHBI), pp 1–7. https://doi.org/10.1109/shbi.2015.7321685. ISBN 978-1-4673-6522-2
50. Passino KM (2002) Biomimicry of bacterial foraging for distributed optimization and control. IEEE Control Syst 22(3):52–67
51. Chen TC, Tsai PW, Chu SC, Pan JS (2007) A novel optimization approach: bacterial-GA foraging. In: Second international conference on innovative computing, information and control, 2007. ICICIC'07, p 391. IEEE, Sept 2007
52. Yang XS (2010) A new metaheuristic bat-inspired algorithm. In: Nature inspired cooperative strategies for optimization (NICSO 2010), pp 65–74
53. Teodorovic D, Dell'Orco M (2005) Bee colony optimization—a cooperative learning approach to complex transportation problems. Adv OR AI Methods Transp 51:60
54. Wedde HF, Farooq M, Zhang Y (2004) BeeHive: an efficient fault-tolerant routing algorithm inspired by honey bee behavior. In: Lecture notes in computer science, vol 3172, pp 83–94
55. Lucic P, Teodorović D (2001) Bee system: modeling combinatorial optimization transportation engineering problems by swarm intelligence. Preprints of the TRISTAN IV triennial symposium on transportation analysis, pp 441–445
56. Pham DT, Ghanbarzadeh A, Koc E, Otri S, Rahim S, Zaidi M (2011) The bees algorithm—a novel tool for complex optimisation. In: Intelligent production machines and systems-2nd I* PROMS virtual international conference, 3–14 July 2006
57. Drias H, Sadeg S, Yahi S (2005) Cooperative bees swarm for solving the maximum weighted satisfiability problem. In: Computational intelligence and bioinspired systems, pp 417–448
58. Comellas F, Martinez-Navarro J (2009) Bumblebees: a multiagent combinatorial optimization algorithm inspired by social insect behaviour. In: Proceedings of the first ACM/SIGEVO summit on genetic and evolutionary computation. ACM, pp 811–814, June 2009
59. Chu S-A, Tsai P-W, Pan J-S (2006) Cat swarm optimization. In: Lecture notes in computer science (including subseries Lecture notes in artificial intelligence and Lecture notes in bioinformatics), LNAI, vol 4099, pp 854–858
60. Iordache S (2010) Consultant-guided search: a new metaheuristic for combinatorial optimization problems. In: Proceedings of the 12th annual conference on Genetic and evolutionary computation. ACM, pp 225–232, July 2010
61. Askarzadeh A (2016) A novel metaheuristic method for solving constrained engineering optimization problems: crow search algorithm. Comput Struct 169:1–12
62. Yang XS, Deb S (2009) Cuckoo search via Lévy flights. In: World Congress on Nature & Biologically Inspired Computing, 2009. NaBIC 2009. IEEE, pp 210–214, Dec 2009
63. Mirjalili S (2016) Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems. Neural Comput Appl 27(4):1053–1073
64. Topal AO, Altun O (2014) A novel meta-heuristic algorithm: dynamic virtual bats algorithm. Inf Sci 354:222–235
65. Yang XS, Deb S (2010) Eagle strategy using Lévy walk and firefly algorithms for stochastic optimization. In: Nature inspired cooperative strategies for optimization (NICSO 2010), pp 101–111
66. Chu Y, Mi H, Liao H, Ji Z, Wu QH (2008) A fast bacterial swarming algorithm for high-dimensional function optimization. In: IEEE Congress on Evolutionary Computation, 2008. CEC 2008 (IEEE World Congress on Computational Intelligence). IEEE, pp 3135–3140, June 2008
67. Yang XS (2010) Firefly algorithm, stochastic test functions and design optimisation. Int J Bio Inspir Comput 2(2):78–84
68. Li LX, Shao ZJ, Qian JX (2002) An optimizing method based on autonomous animals: fish-swarm algorithm. Syst Eng Theory Pract 22:32–38
69. Krishnanand KN, Ghose D (2005) Detection of multiple source locations using a glowworm metaphor with applications to collective robotics. In: Swarm intelligence symposium, 2005. SIS 2005. Proceedings 2005 IEEE. IEEE, pp 84–91, June 2005
70. Krishnanand KN, Ghose D (2009) Glowworm swarm optimisation: a new method for optimising multi-modal functions. Int J Comput Intell Stud 1(1):93–119
71. Su S, Wang J, Fan W, Yin X (2007) Good lattice swarm algorithm for constrained engineering design optimization. In: International conference on wireless communications, networking and mobile computing, 2007. WiCom 2007. IEEE, pp 6421–6424, Sept 2007
72. Saremi S, Mirjalili S, Lewis A (2017) Grasshopper optimisation algorithm: theory and application. Adv Eng Softw 105:30–47
73. Mirjalili S, Mirjalili SM, Lewis A (2014) Grey wolf optimizer. Adv Eng Softw 69:46–61
74. Chen H, Zhu Y, Hu K, He X (2010) Hierarchical swarm model: a new approach to optimization. Discrete Dyn Nat Soc. https://doi.org/10.1155/2010/379649
75. Oftadeh R, Mahjoob MJ (2009) A new meta-heuristic optimization algorithm: hunting search. In: Fifth international conference on soft computing, computing with words and perceptions in system analysis, decision and control, 2009. ICSCCW 2009. IEEE, pp 1–5, Sept 2009
76. Biyanto TR, Irawan S, Febrianto HY, Afdanny N, Rahman AH, Gunawan KS, Pratama JAD, Bethiana TN (2017) Killer whale algorithm: an algorithm inspired by the life of killer whale. Proc Comput Sci 124:151–157

77. Gandomi AH, Alavi AH (2012) Krill herd: a new bio-inspired optimization algorithm. Commun Nonlinear Sci Numer Simul 17(12):4831–4845
78. Mucherino A, Seref O (2007) Monkey search: a novel metaheuristic search for global optimization. In: AIP conference proceedings, vol 953, no. 1, pp 162–173). AIP, Nov 2007
79. Mirjalili S (2015) Moth-flame optimization algorithm: a novel nature-inspired heuristic paradigm. Knowl Based Syst 89:228–249
80. Eberhart R, Kennedy J (1995) A new optimizer using particle swarm theory. In: Proceedings of the sixth international symposium on micro machine and human science, 1995. MHS'95. IEEE, pp 39–43, Oct 1995
81. Mirjalili S, Gandomi AH, Mirjalili SZ, Saremi S, Faris H, Mirjalili SM (2017) Salp swarm algorithm: a bio-inspired optimizer for engineering design problems. Adv Eng Softw 114:163–191
82. Abedinia O, Amjady N, Ghasemi A (2016) A new metaheuristic algorithm based on shark smell optimization. Complexity 21(5):97–116
83. Yang XS, Lees JM, Morley CT (2006) Application of virtual ant algorithms in the optimization of CFRP shear strengthened precracked structures. In: International conference on computational science. Springer, Berlin, pp 834–837, May 2006
84. Yang XS (2005) Engineering optimizations via nature-inspired virtual bee algorithms. In: Artificial intelligence and knowledge engineering applications: a bioinspired approach, pp 317–323
85. Ting TO, Man KL, Guan SU, Nayel M, Wan K (2012) Weightless swarm algorithm (WSA) for dynamic optimization problems. In: NPC, pp 508–515, Sept 2012
86. Mirjalili S, Lewis A (2016) The whale optimization algorithm. Adv Eng Softw 95:51–67
87. Tang R, Fong S, Yang XS, Deb S (2012) Wolf search algorithm with ephemeral memory. In: 2012 seventh international conference on digital information management (ICDIM). IEEE, pp 165–172, Aug 2012
88. Yan GW, Hao ZJ (2013) A novel optimization algorithm based on atmosphere clouds model. Int J Comput Intell Appl 12(01):1350002
89. Simon D (2008) Biogeography-based optimization. IEEE Trans Evol Comput 12(6):702–713
90. Shi Y (2015) An optimization algorithm based on brainstorming process. In: Emerging research on swarm intelligence and algorithm optimization. IGI Global, pp 1–35
91. Eesa AS, Brifcani AMA, Orman Z (2013) Cuttlefish algorithm—a novel bio-inspired optimization algorithm. Int J Sci Eng Res 4(9):1978–1986
92. Kaveh A, Farhoudi N (2013) A new optimization method: dolphin echolocation. Adv Eng Softw 59:53–70
93. Biyanto TR, Fibrianto HY, Nugroho G, Hatta AM, Listijorini E, Budiati T, Huda H (2016) Duelist algorithm: an algorithm inspired by how duelist improve their capabilities in a duel. In: International conference in swarm intelligence. Springer, pp 39–47, June 2016
94. Zheng YJ, Ling HF, Xue JY (2014) Ecogeography-based optimization: enhancing biogeography-based optimization with ecogeographic barriers and differentiations. Comput Oper Res 50:115–127
95. Parpinelli RS, Lopes HS (2011) An eco-inspired evolutionary algorithm applied to numerical optimization. In: 2011 Third World Congress on Nature and Biologically Inspired Computing (NaBIC). IEEE, pp 466–471, Oct 2011
96. Sur C, Sharma S, Shukla A (2013) Egyptian vulture optimization algorithm—a new nature inspired meta-heuristics for knapsack problem. In: The 9th international conference on computing and information technology (IC2IT2013). Springer, Berlin, pp 227–237
97. Bastos Filho CJ, de Lima Neto FB, Lins AJ, Nascimento AI, Lima MP (2008) A novel search algorithm based on fish school behavior. In: IEEE international conference on systems, man and cybernetics, 2008. SMC 2008. IEEE, pp 2646–2651, Oct 2008
98. Bastos Filho CJ, de Lima Neto FB, Lins AJ, Nascimento AI, Lima MP (2009) Fish school search. In: Chiong R (ed) Nature-inspired algorithms for optimisation. Springer, Berlin, pp 261–277
99. Yang XS, Karamanoglu M, He X (2013) Multi-objective flower algorithm for optimization. Proc Comput Sci 18:861–868
100. Ferreira C (2001) Gene expression programming: a new adaptive algorithm for solving problems. arXiv preprint arXiv:cs/0102027
101. Mozaffari A, Fathi A, Behzadipour S (2012) The great salmon run: a novel bio-inspired algorithm for artificial system design and optimisation. Int J Bio Inspir Comput 4(5):286–301
102. He S, Wu QH, Saunders JR (2009) Group search optimizer: an optimization algorithm inspired by animal searching behavior. IEEE Trans Evol Comput 13(5):973–990
103. Zhang LM, Dahlmann C, Zhang Y (2009) Human-inspired algorithms for continuous function optimization. In: IEEE international conference on intelligent computing and intelligent systems, 2009. ICIS 2009, vol 1. IEEE, pp 318–321, Nov 2009
104. Mehrabian AR, Lucas C (2006) A novel numerical optimization algorithm inspired from weed colonization. Ecol Inform 1(4):355–366
105. Hernández H, Blum C (2012) Distributed graph colouring: an approach based on the calling behavior of Japanese tree frogs. Swarm Intell 6(2):117–150
106. Yazdani M, Jolai F (2016) Lion optimization algorithm (LOA): a nature-inspired metaheuristic algorithm. J Comput Des Eng 3(1):24–36
107. Abbass HA (2001) MBO: marriage in honey bees optimization—A haplometrosis polygynous swarming approach. In: Proceedings of the 2001 Congress on Evolutionary Computation, vol 1. IEEE, pp 207–214
108. Asil Gharebaghi S, Ardalan Asl M (2017) New meta-heuristic optimization algorithm using neuronal communication. Iran Univ Sci Technol 7(3):413–431
109. Maia RD, de Castro LN, Caminhas WM (2012) Bee colonies as model for multimodal continuous optimization: the OptBees algorithm. In: 2012 IEEE Congress on Evolutionary Computation (CEC). IEEE, pp 1–8, June 2012
110. Premaratne U, Samarabandu J, Sidhu T (2009) A new biologically inspired optimization algorithm. In: International conference on industrial and information systems (ICIIS). IEEE, pp 279–284, Dec 2009
111. Jung SH (2003) Queen-bee evolution for genetic algorithms. Electron Lett 39(6):575–576
112. Havens TC, Spain CJ, Salmon NG, Keller JM (2008) Roach infestation optimization. In: Swarm intelligence symposium, 2008. SIS 2008. IEEE, pp 1–7, Sept 2008
113. Eusuff MM, Lansey KE (2003) Optimization of water distribution network design using the shuffled frog leaping algorithm. J Water Resour Plan Manag 129(3):210–225
114. Ebrahimi A, Khamehchi E (2016) Sperm whale algorithm: an effective metaheuristic algorithm for production optimization problems. J Nat Gas Sci Eng 29:211–222
115. Dhiman G, Kumar V (2017) Spotted hyena optimizer: a novel bio-inspired based metaheuristic technique for engineering applications. Adv Eng Softw 114:48–70

116. Pattnaik SS, Bakwad KM, Sohi BS, Ratho RK, Devi S (2013) Swine influenza models based optimization (SIMBO). Appl Soft Comput 13(1):628–653
117. Cheng MY, Prayogo D (2014) Symbiotic organisms search: a new metaheuristic optimization algorithm. Comput Struct 139:98–112
118. Hedayatzadeh R, Salmassi FA, Keshtgari M, Akbari R, Ziarati K (2010) Termite colony optimization: a novel approach for optimizing continuous problems. In: 2010 18th Iranian conference on electrical engineering (ICEE). IEEE, pp 553–558, May 2010
119. Jaderyan M, Khotanlou H (2016) Virulence optimization algorithm. Appl Soft Comput 43:596–618
120. Li MD, Zhao H, Weng XW, Han T (2016) A novel nature-inspired algorithm for optimization: virus colony search. Adv Eng Softw 92:65–68
121. Pelikan M (2005) Bayesian optimization algorithm. In: Hierarchical Bayesian optimization algorithm, pp 31–48
122. Zandi Z, Afjei E, Sedighizadeh M (2012) Reactive power dispatch using big bang-big crunch optimization algorithm for voltage stability enhancement. In: 2012 IEEE international conference on power and energy (PECon). IEEE, pp 239–244, Dec 2012
123. Hatamlou A (2013) Black hole: a new heuristic optimization approach for data clustering. Inf Sci 222:175–184
124. Richard A (2007) Formato. Central force optimization: a new metaheuristic with applications in applied electromagnetics. Prog Electromagn Res 77:425–491
125. Kaveh A, Talatahari S (2010) A novel heuristic optimization method: charged system search. Acta Mechan 213:267
126. Salmani MH, Eshghi K (2017) A metaheuristic algorithm based on chemotherapy science: CSA. J Optim. https://doi.org/10.1155/2017/3082024
127. Kaveh A, Mahdavi VR (2014) Colliding bodies optimization: a novel meta-heuristic method. Comput Struct 139:18–27
128. Cuevas E, Oliva D, Zaldivar D, Pérez-Cisneros M, Sossa H (2012) Circle detection using electro-magnetism optimization. Inf Sci 182(1):40–55
129. Kaedi M (2017) Fractal-based algorithm: a new metaheuristic method for continuous optimization. Int J Artif Intell 15(1):76–92
130. Shah-Hosseini H (2011) Principal components analysis by the galaxy-based search algorithm: a novel metaheuristic for continuous optimisation. Int J Comput Sci Eng 6(1–2):132–140
131. Rashedi E, Nezamabadi-Pour H, Saryazdi S (2009) GSA: a gravitational search algorithm. Inf Sci 179(13):2232–2248
132. Geem ZW, Kim JH, Loganathan GV (2001) A new heuristic optimization algorithm: harmony search. Simulation 76(2):60–68
133. Wedyan A, Whalley J, Narayanan A (2017) Hydrological cycle algorithm for continuous optimization problems. J Optim. https://doi.org/10.1155/2017/3828420
134. Hosseini HS (2007) Problem solving by intelligent water drops. In: IEEE Congress on Evolutionary Computation, 2007. CEC 2007. IEEE, pp 3226–3231, Sept 2007
135. Javidy B, Hatamlou A, Mirjalili S (2015) Ions motion algorithm for solving optimization problems. Appl Soft Comput 32:72–79
136. https://en.wikiversity.org/wiki/Algorithms/Mass_and_Energy_Balances_Algorithm. Accessed 11 Jan 2018
137. Kashan AH (2015) A new metaheuristic for optimization: optics inspired optimization (OIO). Comput Oper Res 55:99–125
138. Biyanto TR, Syamsi MN, Fibrianto HY, Afdanny N, Rahman AH, Gunawan KS, Pratama JA, Malwindasari A, Abdillah AI, Bethiana TN, Putra YA (2017) Optimization of energy efficiency and conservation in green building design using duelist, killer-whale and rain-water algorithms. In: IOP conference series: materials science and engineering, vol 267, no. 1. IOP Publishing, p 012036, Nov 2017
139. Kaboli SHA, Selvaraj J, Rahim NA (2017) Rain-fall optimization algorithm: a population based algorithm for solving constrained optimization problems. J Computational Sci 19:31–42
140. Rabanal P, Rodríguez I, Rubio F (2007) Using river formation dynamics to design heuristic algorithms. In: Unconventional computation, pp 163–177
141. Vicsek T, Czirók A, Ben-Jacob E, Cohen I, Shochet O (1995) Novel type of phase transition in a system of self-driven particles. Phys Rev Lett 75(6):1226
142. Kirkpatrick S, Gelatt CD, Vecchi MP (1983) Optimization by simulated annealing. Science 220(4598):671–680
143. Ibrahim A, Rahnamayan S, Martin MV (2014) Simulated raindrop algorithm for global optimization. In: 2014 IEEE 27th Canadian conference on electrical and computer engineering (CCECE). IEEE, pp 1–8, May 2014
144. Mirjalili S (2016) SCA: a sine cosine algorithm for solving optimization problems. Knowl Based Syst 96:120–133
145. Tzanetos A, Dounias G (2017) A new metaheuristic method for optimization: sonar inspired optimization. In: Boracchi G, Iliadis L, Jayne C, Likas A (eds) Engineering applications of neural networks. EANN 2017 communications in computer and information science, vol 744. Springer, Cham
146. Tamura K, Yasuda K (2011) Spiral dynamics inspired optimization. J Adv Comput Intell Intell Inform 15(8):1116–1122
147. Bishop JM (1989) Stochastic searching networks. In: First IEE international conference on artificial neural networks (conference publication no. 313). IET, pp 329–331, Oct 1989
148. Kaveh A, Dadras A (2017) A novel meta-heuristic optimization algorithm: thermal exchange optimization. Adv Eng Softw 110:69–84
149. Doğan B, Ölmez T (2015) A new metaheuristic for numerical function optimization: vortex search algorithm. Inf Sci 293:125–145
150. Eskandar H, Sadollah A, Bahreininejad A, Hamdi M (2012) Water cycle algorithm—a novel metaheuristic optimization method for solving constrained engineering optimization problems. Comput Struct 110:151–166
151. Zheng YJ (2015) Water wave optimization: a new nature-inspired metaheuristic. Comput Oper Res 55:1–11
152. Friedl G, Kuczmann M (2015) A new metaheuristic optimization algorithm, the weighted attraction method. Acta Tech Jaurinensis 8(3):257–266
153. Hasançebi O, Azad SK (2015) Adaptive dimensional search: a new metaheuristic algorithm for discrete truss sizing optimization. Comput Struct 154:1–16
154. Shayeghi H, Dadashpour J (2012) Anarchic society optimization based PID control of an automatic voltage regulator (AVR) system. Electr Electron Eng 2(4):199–207
155. Civicioglu P (2013) Artificial cooperative search algorithm for numerical optimization problems. Inf Sci 229:58–76
156. Civicioglu P (2013) Backtracking search optimization algorithm for numerical optimization problems. Appl Math Comput 219(15):8121–8144
157. Kim JH, Choi YH, Ngo TT, Choi J, Lee HM, Choo YM, Lee EH, Yoo DG, Sadollah A, Jung D (2016) KU battle of metaheuristic optimization algorithms 1: development of six new/improved algorithms. In: Kim J, Geem Z (eds) Harmony search algorithm. Springer, Berlin, pp 197–205
158. Civicioglu P (2012) Transforming geocentric cartesian coordinates to geodetic coordinates by using differential search algorithm. Comput Geosci 46:229–247
159. Azad SK, Hasançebi O (2014) An elitist self-adaptive step-size search for structural design optimization. Appl Soft Comput 19:226–235

160. Fadakar E, Ebrahimi M (2016) A new metaheuristic football game inspired algorithm. In: 2016 1st conference on swarm intelligence and evolutionary computation (CSIEC). IEEE, pp 6–11, Mar 2016
161. Ryan C, Collins JJ, Neill MO (1998) Grammatical evolution: evolving programs for an arbitrary language. In: European conference on genetic programming. Springer, Berlin, pp 83–96, Apr 1998
162. Azad SK, Hasançebi O, Saka MP (2014) Guided stochastic search technique for discrete sizing optimization of steel trusses: a design-driven heuristic approach. Comput Struct 134:62–74
163. Atashpaz-Gargari E, Lucas C (2007) Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition. In: IEEE Congress on Evolutionary Computation, 2007. CEC 2007. IEEE, pp 4661–4667, Sept 2007
164. Kashan AH (200) League championship algorithm: a new algorithm for numerical function optimization. In: International conference of soft computing and pattern recognition, 2009. SOCPAR'09. IEEE, pp 43–48 Dec 2000
165. Savsani P, Savsani V (2016) Passing vehicle search (PVS): a novel metaheuristic algorithm. Appl Math Model 40(5):3951–3978
166. Gonçalves MS, Lopez RH, Miguel LFF (2015) Search group algorithm: a new metaheuristic method for the optimization of truss structures. Comput Struct 153:165–184
167. Xu Y, Cui Z, Zeng J (2010) Social emotional optimization algorithm for nonlinear constrained optimization problems. In: SEMCCO, pp 583–590, Jan 2010
168. Glover F (1989) Tabu search—part I. ORSA J Comput 1(3):190–206
169. Glover F (1990) Tabu search—part II. ORSA J Comput 2(1):4–32
170. Rao RV, Savsani VJ, Vakharia DP (2012) Teaching–learning-based optimization: an optimization method for continuous non-linear large scale problems. Inf Sci 183(1):1–15
171. Razmjooy N, Khalilpour M, Ramezani M (2016) A new meta-heuristic optimization algorithm inspired by FIFA World Cup competitions: theory and its application in PID designing for AVR system. J Control Autom Electr Syst 27(4):419–440
172. Punnathanam V, Kotecha P (2016) Yin-Yang-pair optimization: a novel lightweight optimization algorithm. Eng Appl Artif Intell 54:62–79
173. Price KV (1999) An introduction to differential evolution. In: Corne D, Dorigo M, Glover F (eds) New ideas in optimization. McGraw-Hill, London, pp 79–108
174. Price KV, Storn RM, Lampinen JA (2005) Differential evolution a practical approach to global optimization. Springer, Berlin
175. Storn R, Price K (1997) Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces. J Glob Optim 11(4):341–359
176. Beyer HG, Schwefel HP (2002) Evolution strategies—a comprehensive introduction. Nat Comput 1(1):3–52
177. Michalewicz Z (1996) Evolution strategies and other methods. In: Genetic algorithms + data structures = evolution programs. Springer, Berlin, pp 159–177
178. Back T, Fogel DB, Michalewicz Z (1997) Handbook of evolutionary computation. IOP Publishing, Bristol
179. Fogel DB (1993) Applying evolutionary programming to selected traveling salesman problems. Cybern Syst 24(1):27–36
180. Yao X, Liu Y, Lin G (1999) Evolutionary programming made faster. IEEE Trans Evol Comput 3(2):82–102
181. Goldberg DE, Holland JH (1988) Genetic algorithms and machine learning. Mach Learn 3(2):95–99
182. Holland JH (1992) Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control and artificial intelligence. MIT Press, Cambridge
183. Koza JR (1992) Genetic programming, vol 1: on the programming of computers by means of natural selection. MIT Press, Cambridge
184. Koza JR (1994) Genetic programming as a means for programming computers by natural selection. Statistics and Computing 4(2):87–112
185. Koza JR, Bennett FH III, Stiffelman O (1999) Genetic programming as a Darwinian invention machine. Springer, Berlin
186. Yang XS, He X (2016) Nature-inspired optimization algorithms in engineering: overview and applications. In: Yang XS (ed) Nature-inspired computation in engineering. Springer, Berlin, pp 1–20
187. Booker L (ed) (2005) Perspectives on adaptation in natural and artificial systems, vol 8. Oxford University Press on Demand, Oxford
188. Fister I, Yang XS, Brest J, Fister I Jr (2014) On the randomized firefly algorithm. In: Yang XS (ed) Cuckoo search and firefly algorithm. Springer, Berlin, pp 27–48
189. Črepinšek M, Liu SH, Mernik M (2013) Exploration and exploitation in evolutionary algorithms: a survey. ACM Comput Surv (CSUR) 45(3):35
190. Črepinšek M, Mernik M, Liu SH (2011) Analysis of exploration and exploitation in evolutionary algorithms by ancestry trees. Int J Innov Comput Appl 3(1):11–19
191. Eiben AE, Schippers CA (1998) On evolutionary exploration and exploitation. Fundam Inform 35(1–4):35–50
192. Walton S, Hassan O, Morgan K, Brown MR (2011) Modified cuckoo search: a new gradient free optimisation algorithm. Chaos Solitons Fractals 44(9):710–718
193. Walton S, Hassan O, Morgan K, Brown MR (2013) A review of the development and applications of the cuckoo search algorithm. In: Yang X-S, Cui Z, Xiao R, Gandomi AH, Karamanoglu M (eds) Swarm intelligence and bio-inspired computation. Elsevier, Amsterdam, pp 257–271
194. Bansal JC, Singh PK, Saraswat M, Verma A, Jadon SS, Abraham A (2011) Inertia weight strategies in particle swarm optimization. In: Third World Congress on Nature and Biologically Inspired Computing, pp 640–647
195. Yang X, Yuan J, Yuan J, Mao H (2007) A modified particle swarm optimizer with dynamic adaptation. Appl Math Comput 189(2):1205–1213
196. Fister I, Yang XS, Brest J, Fister I Jr (2013) Memetic self-adaptive firefly algorithm. In: Swarm intelligence and bio-inspired computation: theory and applications, pp 73–102. https://doi.org/10.1016/b978-0-12-405163-8.00004-1
197. Saitoh F (1999) Image contrast enhancement using genetic algorithm. In: 1999 IEEE international conference on systems, man, and cybernetics, 1999. IEEE SMC'99 conference proceedings, vol 4, pp 899–904. IEEE
198. Zhang C, Wang X, Duanmu C (2010) Adaptive typhoon cloud image enhancement using genetic algorithm and non-linear gain operation in undecimated wavelet domain. Eng Appl Artif Intell 23(1):61–73
199. Zhang J, Li H, Tang Z, Lu Q, Zheng X, Zhou J (2014) An improved quantum-inspired genetic algorithm for image multilevel thresholding segmentation. Math Probl Eng. https://doi.org/10.1155/2014/295402
200. Lee MC, Cho SB (2012) Interactive differential evolution for image enhancement application in smart phone. In: 2012 IEEE Congress on Evolutionary Computation (CEC). IEEE, pp 1–6, June 2012
201. Bhandari AK, Kumar A, Chaudhary S, Singh GK (2017) A new beta differential evolution algorithm for edge preserved coloured satellite image enhancement. Multidimens Syst Signal Process 28(2):495–527

202. dos Santos Coelho L, Sauer JG, Rudek M (2009) Differential evolution optimization combined with chaotic sequences for image contrast enhancement. Chaos Solitons Fractals 42(1):522–529
203. Sarangi PP, Mishra BSP, Majhi B, Dehuri S (2014) Gray-level image enhancement using differential evolution optimization algorithm. In 2014 international conference on signal processing and integrated networks (SPIN). IEEE, pp 95–100, Feb 2014
204. Oh J, Hwang H (2010) Feature enhancement of medical images using morphology-based homomorphic filter and differential evolution algorithm. Int J Control Autom Syst 8(4):857–861
205. Suresh S, Lal S (2017) Modified differential evolution algorithm for contrast and brightness enhancement of satellite images. Appl Soft Comput 61:622–641
206. Sarkar S, Paul S, Burman R, Das S, Chaudhuri SS (2014) A fuzzy entropy based multi-level image thresholding using differential evolution. In: International conference on swarm, evolutionary, and memetic computing. Springer, pp 386–395, Dec 2014
207. Sarkar S, Das S, Chaudhuri SS (2015) A multilevel colour image thresholding scheme based on minimum cross entropy and differential evolution. Pattern Recognit Lett 54:27–35
208. Munteanu C, Rosa A (2004) Gray-scale image enhancement as an automatic process driven by evolution. IEEE Trans Syst Man Cybern Part B (Cybern) 34(2):1292–1298
209. Mohamad ZS, Darvish A, Rahnamayan S (2011) Eye illusion enhancement using interactive differential evolution. In: 2011 IEEE symposium on differential evolution (SDE). IEEE, pp 1–7, Apr 2011
210. Kwok NM, Shi HY, Ha QP, Fang G, Chen SY, Jia X (2013) Simultaneous image colour correction and enhancement using particle swarm optimization. Eng Appl Artif Intell 26(10):2356–2371
211. Saitoh F (2001) Local contrast enhancement by optimizing image separation using genetic algorithm. IEEJ Trans Electron Inf Syst 121(10):1508–1515
212. Goel S, Verma A, Kumar N (2013) Gray level enhancement to emphasize less dynamic region within image using genetic algorithm. In 2013 IEEE 3rd international advance computing conference (IACC). IEEE, pp 1171–1176, Feb 2013
213. Hashemi S, Kiani S, Noroozi N, Moghaddam ME (2010) An image contrast enhancement method based on genetic algorithm. Pattern Recognit Lett 31(13):1816–1824
214. Pal SK, Bhandari D, Kundu MK (1994) Genetic algorithms for optimal image enhancement. Pattern Recognit Lett 15(3):261–271
215. Zhang C, Wang X (2006) Global and local contrast enhancement for image by genetic algorithm and wavelet neural network. In: Neural information processing, pp 910–919. Springer, Berlin
216. Lukac R, Plataniotis KN, Smolka B, Venetsanopoulos AN (2004) Colour image filtering and enhancement based genetic algorithms. In: Proceedings of the 2004 international symposium on circuits and systems, 2004. ISCAS'04, vol 3. IEEE, pp III–913, May 2004
217. Jiang DH, Hua G (2015) Research on image enhancement method based on adaptive immune genetic algorithm. J Comput Theor Nanosci 12(1):119–127
218. Shyu MS, Leou JJ (1998) A genetic algorithm approach to colour image enhancement. Pattern Recognit 31(7):871–880
219. Daniel E, Anitha J (2015) Optimum green plane masking for the contrast enhancement of retinal images using enhanced genetic algorithm. Optik Int J Light Electron Opt 126(18):1726–1730
220. Sarangi PP, Mishra BSP, Majhi B, Dehuri S (2014) Gray-level image enhancement using differential evolution optimization algorithm. In: 2014 international conference on signal processing and integrated networks (SPIN). IEEE, pp 95–100, Feb 2014
221. Nickfarjam AM, Ebrahimpour-Komleh H (2017) Multi-resolution gray-level image enhancement using particle swarm optimization. Appl Intell 47:1132
222. Shanmugavadivu P, Balasubramanian K, Muruganandam A (2014) Particle swarm optimized bi-histogram equalization for contrast enhancement and brightness preservation of images. Vis Comput 30(4):387–399
223. Abdullahi MB, Idris F, Mohammed AA (2016) Performance analysis of particle swarm optimization algorithm-based parameter tuning for fingerprint image enhancement. In: future technologies conference (FTC). IEEE, pp 528–536, Dec 2016
224. Verma HK, Pal S (2016) Modified sigmoid function based gray scale image contrast enhancement using particle swarm optimization. J Inst Eng (India) Ser B 97(2):243–251
225. Singh RP, Dixit M, Silakari S (2014) Image contrast enhancement using GA and PSO: a survey. In: 2014 international conference on computational intelligence and communication networks (CICN). IEEE, pp 186–189, Nov 2014
226. Masra SMW, Pang PK, Muhammad MS, Kipli K (2012) Application of particle swarm optimization in histogram equalization for image enhancement. In: 2012 IEEE colloquium on humanities, science and engineering (CHUSER). IEEE, pp 294-299, Dec 2012
227. Rani MMS, Mary GG (2017) Particle swarm optimization based image enhancement of visual cryptography shares. In: Lu H, Li Y (eds) Artificial intelligence and computer vision. Springer, Berlin, pp 31–49
228. Quraishi MI, De M, Dhal KG, Mondal S, Das G (2013) A novel hybrid approach to restore historical degraded documents. In: 2013 international conference on intelligent systems and signal processing (ISSP). IEEE, pp 185–189, Mar 2013
229. Gorai A, Ghosh A (2009) Gray-level image enhancement by particle swarm optimization. In: World Congress on Nature & Biologically Inspired Computing, 2009. NaBIC 2009. IEEE, pp 72–77, Dec 2009
230. Zhang T, Wan L, Xu Y, Lu Y (2008) Sonar image enhancement based on particle swarm optimization. In: 3rd IEEE conference on industrial electronics and applications, 2008. ICIEA 2008. IEEE, pp 2216–2221, June 2008
231. Braik M, Sheta A, Ayesh A (2007) Particle swarm optimisation enhancement approach for improving image quality. Int J Innov Comput Appl 1(2):138–145
232. Qinqing G, Dexin C, Guangping Z, Ketai H (2011) Image enhancement technique based on improved PSO algorithm. In: 2011 6th IEEE conference on industrial electronics and applications (ICIEA). IEEE, pp 234–238, June 2011
233. Venkatalakshmi K, Shalinie SM (2010) A customized particle swarm optimization algorithm for image enhancement. In: 2010 IEEE international conference on communication control and computing technologies (ICCCCT). IEEE, pp 603–607, Oct 2010
234. Quraishi MI, Dhal KG, Choudhury JP, Pattanayak K, De M (2012) A novel hybrid approach to enhance low resolution images using particle swarm optimization. In: 2012 2nd IEEE international conference on parallel distributed and grid computing (PDGC). IEEE, pp 888–893, Dec 2012
235. Dhal KG, Quraishi MdI, Das S (2016) Gray level image enhancement using particle swarm optimization with Lévy flight: a hybrid approach. Int J Innov Res Sci Eng Technol 5(13):79–86
236. Kwok NM, Ha QP, Liu D, Fang G (2009) Contrast enhancement and intensity preservation for gray-level images using multiobjective particle swarm optimization. IEEE Trans Autom Sci Eng 6(1):145–155

237. Chen H, Tian J (2011) Using particle swarm optimization algorithm for image enhancement. In: 2011 international conference on uncertainty reasoning and knowledge engineering (URKE), vol 1. IEEE, pp 154–157, Aug 2011
238. Gorai A, Ghosh A (2011) Hue-preserving colour image enhancement using particle swarm optimization. In: recent advances in intelligent computational systems (RAICS). IEEE, pp 563–568, Sept 2011
239. Subhashdas SK, Choi BS, Yoo JH, Ha YH (2015) Colour image enhancement based on particle swarm optimization with Gaussian mixture. In: Colour imaging XX: displaying, processing, hardcopy, and applications, vol 9395. International Society for Optics and Photonics, p 939508, Feb 2015
240. Hanmadlu M, Arora S, Gupta G, Singh L (2013) A novel optimal fuzzy colour image enhancement using particle swarm optimization. In: 2013 sixth international conference on contemporary computing (IC3). IEEE, pp 41–46, Aug 2013
241. Sharma N, Verma OP (2017) Estimation of weighting distribution using fuzzy memberships and wavelet transformation with PSO optimization in satellite image enhancement. Cogent Eng 4(1):1392835
242. Mohan S, Mahesh TR (2013) Particle swarm optimization based contrast limited enhancement for mammogram images. In: 2013 7th international conference on intelligent systems and control (ISCO). IEEE, pp 384–388, Jan 2013
243. Singh H, Kumar A, Balyan LK, Singh GK (2017) Swarm intelligence optimized piecewise gamma corrected histogram equalization for dark image enhancement. Comput Electr Eng. https://doi.org/10.1016/j.compeleceng.2017.06.029
244. Kanmani M, Narsimhan V (2018) An image contrast enhancement algorithm for grayscale images using particle swarm optimization. Multimed Tools Appl 77(18):1–17
245. Kanmani M, Narasimhan V (2017) Swarm intelligent based contrast enhancement algorithm with improved visual perception for colour images. Multimed Tools Appl 77:12701
246. Verma OP, Kumar P, Hanmandlu M, Chhabra S (2012) High dynamic range optimal fuzzy colour image enhancement using artificial ant colony system. Appl Soft Comput 12(1):394–404
247. Hoseini P, Shayesteh MG (2013) Efficient contrast enhancement of images using hybrid ant colony optimisation, genetic algorithm, and simulated annealing. Digit Signal Process 23(3):879–893
248. Gao H, Zeng W (2015) Colour image enhancement based on ant colony optimization algorithm. TELKOMNIKA 13(1):155–163
249. Pan B (2014) Application of ant colony mixed algorithm in image enhancement. Comput Model New Technol 18(12b):529–534
250. Hanmandlu M, Verma OP, Kumar NK, Kulkarni M (2009) A novel optimal fuzzy system for colour image enhancement using bacterial foraging. IEEE Trans Instrum Meas 58(8):2867–2879
251. Verma OP, Chopra RR, Gupta A (2016) An adaptive bacterial foraging algorithm for colour image enhancement. In: 2016 annual conference on information science and systems (CISS). IEEE, pp 1–6, Mar 2016
252. Hassanzadeh T, Vojodi H, Mahmoudi F (2011) Non-linear grayscale image enhancement based on firefly algorithm. In: Swarm, evolutionary, and memetic computing, pp 174–181
253. Katiyar S, Patel R, Arora K (2016) Comparison and analysis of cuckoo search and firefly algorithm for image enhancement. In: International conference on smart trends for information technology and computer communications. Springer, Singapore, pp 62–68, Aug 2016
254. Ye Z, Zhao W, Ma L (2015) An adaptive image enhancement technique based on firefly algorithm. In: 2015 8th international symposium on computational intelligence and design (ISCID), vol 1. IEEE, pp 236–239, Dec 2015
255. Yimit A, Hagihara Y, Miyoshi T, Hagihara Y (2013) Automatic image enhancement by artificial bee colony algorithm. In: International conference on graphic and image processing (ICGIP 2012). Society of Photo-Optical Instrumentation Engineers, Mar 2013
256. Joshi P, Prakash S (2015) An efficient technique for image contrast enhancement using artificial bee colony. In: 2015 IEEE international conference on identity, security and behavior analysis (ISBA). IEEE, pp 1–6, Mar 2015
257. Draa A, Bouaziz A (2014) An artificial bee colony algorithm for image contrast enhancement. Swarm Evol Comput 16:69–84
258. Benala TR, Villa SH, Jampala SD, Konathala B (2009) A novel approach to image edge enhancement using artificial bee colony optimization algorithm for hybridized smoothening filters. In World Congress on Nature & Biologically Inspired Computing, 2009. NaBIC 2009. IEEE, pp 1071–1076, Dec 2009
259. Bhandari AK, Soni V, Kumar A, Singh GK (2014) Artificial bee colony-based satellite image contrast and brightness enhancement technique using DWT-SVD. Int J Remote Sens 35(5):1601–1624
260. Chen J, Yu W, Tian J, Chen L, Zhou Z (2017) Image contrast enhancement using an artificial bee colony algorithm. Swarm Evol Comput 38:287
261. Agrawal S, Panda R (2012) An efficient algorithm for gray level image enhancement using cuckoo search. In: SEMCCO, pp 82–89, Dec 2012
262. Saini MK, Narang D (2013) Cuckoo optimization algorithm based image enhancement. In: Proceedings of international conference on advances in signal processing and communication. Elsevier
263. Bouaziz A, Draa A, Chikhi S (2014) A cuckoo search algorithm for fingerprint image contrast enhancement. In: 2014 second world conference on complex systems (WCCS). IEEE, pp 678–685, Nov 2014
264. Babu RK, Sunitha KVN (2015) Enhancing digital images through cuckoo search algorithm in combination with morphological operation. J Comput Sci 11(1):7
265. Maurya L, Mahapatra PK, Saini G (2016) Modified cuckoo search-based image enhancement. In: Proceedings of the 4th international conference on frontiers in intelligent computing: theory and applications (FICTA). Springer India, pp 625–634
266. Bhandari AK, Soni V, Kumar A, Singh GK (2014) Cuckoo search algorithm based satellite image contrast and brightness enhancement using DWT–SVD. ISA Trans 53(4):1286–1296
267. Biswas B, Roy P, Choudhuri R, Sen BK (2015) Microscopic image contrast and brightness enhancement using multi-scale retinex and cuckoo search algorithm. Proc Comput Sci 70:348–354
268. Ashour AS, Samanta S, Dey N, Kausar N, Abdessalemkaraa WB, Hassanien AE (2015) Computed tomography image enhancement using cuckoo search: a log transform based approach. J Signal Inf Process 6(03):244
269. Daniel E, Anitha J (2016) Optimum wavelet based masking for the contrast enhancement of medical images using enhanced cuckoo search algorithm. Comput Biol Med 71:149–155
270. Tuba M, Jordanski M, Arsic A (2017) Improved weighted thresholded histogram equalization algorithm for digital image contrast enhancement using the bat algorithm. In: Bio-inspired computation and applications in image processing, pp 61–86
271. Bouaziz A, Draa A, Chikhi S (2015) Bat algorithm for fingerprint image enhancement. In: 2015 12th international symposium on programming and systems (ISPS). IEEE, pp 1–8, Apr 2015
272. Zeng Z, Lu L, Wang Y (2013) An enhancement of ladar image based on SFLA algorithm. In: 3rd international conference on multimedia technology (ICMT-13). Atlantis Press, Nov 2013

273. Al-Betar MA, Alyasseri ZAA, Khader AT, Bolaji ALA, Awadallah MA (2016) Gray image enhancement using harmony search. Int J Comput Intell Syst 9(5):932–944
274. Alkareem YZA, Venkat I, Al-Betar MA, Khader AT (2012) Edge preserving image enhancement via harmony search algorithm. In: 2012 4th conference on data mining and optimization (DMO). IEEE, pp 47–52, Sept 2012
275. Zhang C, Wang X, Zhang H (2005) Contrast enhancement for image with simulated annealing algorithm and wavelet neural network. In: Advances in neural networks. ISNN 2005, pp 812–812
276. Zhao W (2011) Adaptive image enhancement based on gravitational search algorithm. Proc Eng 15:3288–3292
277. Sharma A, Kapur RK (2016) Image enhancement using hybrid GSA—particle swarm optimization. In: Contemporary computing and informatics, Dec 2016
278. Yaghoobi S, Hemayat S, Mojallali H (2015) Image gray-level enhancement using black hole algorithm. In: 2015 2nd international conference on pattern recognition and image analysis (IPRIA). IEEE, Mar 2015, pp 1–5
279. Kaushal M, Khehra BS, Sharma A (2017) Water cycle algorithm based multi-objective contrast enhancement approach. Optik Int J Light Electron Opt 140:762–775
280. Ye Z, Wang M, Hu Z, Liu W (2015) An adaptive image enhancement technique by combining cuckoo search and particle swarm optimization algorithm. Comput Intell Neurosci 2015:13
281. Gan L, Duan H (2014) Biological image processing via chaotic differential search and lateral inhibition. Optik Int J Light Electron Opt 125(9):2070–2075
282. Stephen MJ, Prasad Reddy PV (2013) Simple league championship algorithm. Int J Comput Appl 75(6):28–32
283. Mu D, Xu C, Ge H (2011) Hybrid genetic algorithm based image enhancement technology. In: 2011 international conference on internet technology and applications (iTAP). IEEE, pp 1–4, Aug 2011
284. Gatta C, Rizzi A, Marini D (2002) Ace: an automatic colour equalization algorithm. In: Conference on colour in graphics, imaging, and vision, no. 1. Society for Imaging Science and Technology, pp 316–320, Jan 2002
285. Mahapatra PK, Ganguli S, Kumar A (2015) A hybrid particle swarm optimization and artificial immune system algorithm for image enhancement. Soft Comput 19(8):2101–2109
286. Mondal SK, Chatterjee A, Tudu B (2017) Image contrast enhancement using a crossover-included hybrid artificial bee colony optimization. In: Computer, communication and electrical technology: proceedings of the international conference on advancement of computer communication and electrical technology (ACCET 2016), West Bengal, India. CRC Press, 21–22 Oct 2016, p 49, Mar 2017
287. Dhal KG, Sen M, Ray S, Das S (2018) Multi-thresholded histogram equalization based on parameterless artificial bee colony. In: Khosrow-Pour M (ed) Incorporating nature-inspired paradigms in computational applications. IGI Global, pp 108–126
288. Draa A, Benayad Z, Djenna FZ (2015) An opposition-based firefly algorithm for medical image contrast enhancement. Int J Inf Commun Technol 7(4–5):385–405
289. Suresh S, Lal S, Reddy CS, Kiran MS (2017) A novel adaptive cuckoo search algorithm for contrast enhancement of satellite images. IEEE J Sel Top Appl Earth Obs Remote Sens 10:3665
290. Dhal KG, Sen M, Das S (2018) Cuckoo search based modified bi-histogram equalization method to enhance the cancerous tissues in mammography images. Int J Med Eng Inform 10:164
291. Dhal KG, Quraishi MI, Das S (2015) Performance analysis of chaotic Lévy bat algorithm and chaotic cuckoo search algorithm for gray level image enhancement. In: Mandal J, Satapathy S, Kumar Sanyal M, Sarkar P, Mukhopadhyay A (eds) Information systems design and intelligent applications. Springer, New Delhi, pp 233–244
292. Dhal KG, Quraishi I, Das S (2015) A chaotic Lévy flight approach in bat and firefly algorithm for gray level image enhancement. Int J Image Graph Signal Process 7(7):69
293. Dhal KG, Das S (2017) Local search based dynamically adapted bat algorithm in image enhancement domain. Int J Comput Sci Math **(accepted)**. http://www.inderscience.com/info/ingeneral/forthcoming.php?jcode=ijcsm
294. Dhal KG, Quraishi MI, Das S (2015) Performance enhancement of differential evolution by incorporating Lévy flight and chaotic sequence for the cases of satellite images. Int J Appl Metaheuristic Comput 6(3):69–81
295. Dhal KG, Das S (2017) Colour retinal images enhancement using modified histogram equalization methods and firefly algorithm. Int J Biomed Eng Technol. ISSN 1752-6426
296. Dhal KG, Das S (2018) Chaotic differential-evolution-based fuzzy contrast stretching method. In: Dey N (ed) Advancements in applied metaheuristic computing. IGI Global, pp 71–94. https://doi.org/10.4018/978-1-5225-4151-6.ch003
297. Dhal KG, Das S (2017) Cuckoo search with search strategies and proper objective function for brightness preserving image enhancement. Pattern Recognit Image Anal 27(4):695–712
298. Dhal KG, Das S (2018) A dynamically adapted and weighted bat algorithm in image enhancement domain. Evol Syst. https://doi.org/10.1007/s12530-018-9216-1
299. Dhal KG, Das S (2015) Diversity conserved chaotic artificial bee colony algorithm based brightness preserved histogram equalization and contrast stretching method. Int J Nat Comput Res 5(4):45–73
300. Dhal KG, Quraishi MI, Das S (2017) An improved cuckoo search based optimal ranged brightness preserved histogram equalization and contrast stretching method. Int J Swarm Intell Res 8(1):1–29
301. Dhal KG, Quraishi MI, Das S (2016) Development of firefly algorithm via chaotic sequence and population diversity to enhance the image contrast. Nat Comput 15(2):307–318
302. Aja-Fernández S, San José Estépar R, Alberola-López C, Westin CF (2006) Image quality assessment based on local variance. In: EMBC 2006, New York, Sept 2006
303. Eskicioglu AM, Fisher PS (1995) Image quality measures and their performance. IEEE Trans Commun 43(12):2959–2965
304. Wang Z, Bovi AC (2002) A universal image quality index. IEEE Signal Process Lett 9:81–84
305. Wang Z, Bovik AC, Sheikh HR, Simoncelli EP (2004) Image quality assessment: from error visibility to structural similarity. IEEE Trans Image Process 13(4):600–612
306. Hore A, Ziou D (2010) Image quality metrics: PSNR vs. SSIM. In: 2010 20th international conference on pattern recognition (ICPR). IEEE, pp 2366–2369, Aug 2010
307. Zhang L, Zhang L, Mou X, Zhang D (2011) FSIM: A feature similarity index for image quality assessment. IEEE Trans Image Process 20(8):2378–2386
308. Xue W, Zhang L, Mou X, Bovik AC (2014) Gradient magnitude similarity deviation: an highly efficient perceptual image quality index. IEEE Trans Image Process 23:684
309. Haralick RM (1979) Statistical and structural approaches to texture. Proc IEEE 67(5):786–804
310. Gao C, Panetta K, Agaian S (2013) No reference colour image quality measures. In: 2013 international conference on cybernetics, pp 243–248
311. Panetta K, Gao C, Agaian S (2013) No reference colour image contrast and quality measures. IEEE Trans Consum Electron 59:643–651

312. Gupta P, Srivastava P, Bhardwaj S, Bhateja V (2011) A modified PSNR metric based on HVS for quality assessment of colour images. In: 2011 international conference on communication and industrial application (ICCIA), pp 1–4
313. Ponomarenko N, Silvestri F, Egiazarian K, Carli M, Astola J, Lukin V (2007) On between-coefficient contrast masking of DCT basis functions. In: Proceedings of the third international workshop on video processing and quality metrics, USA, CD-ROM
314. Kwok NM, Ha QP, Liu DK, Fang G (2006) Intensity-preserving contrast enhancement for gray-level images using multi-objective particle swarm optimization. In: IEEE international conference on automation science and engineering, 2006. CASE'06. IEEE, pp 21–26, Oct 2006
315. Peng R, Varshney PK (2013) Noise-refined image enhancement using multi-objective optimisation. IET Image Process 7(3):191–200
316. Quraishi MI, Dhal KG, Das G (2012) A comparative study on image edge enhancement for synthetic aperture radar (SAR) images. Trends Innov Comput, pp 211–215. https://pdfs.semanticscholar.org/24b8/a60d2479913f9088e30ae52303684a88a307.pdf