



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
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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 its 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:

$$s = T(r) \quad (2)$$

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 formulating 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

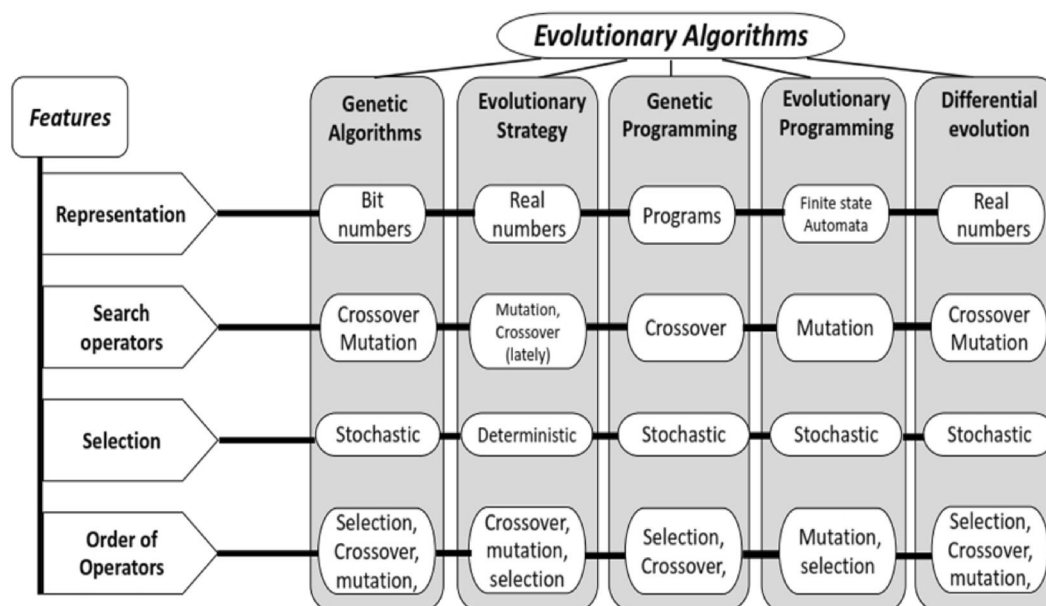
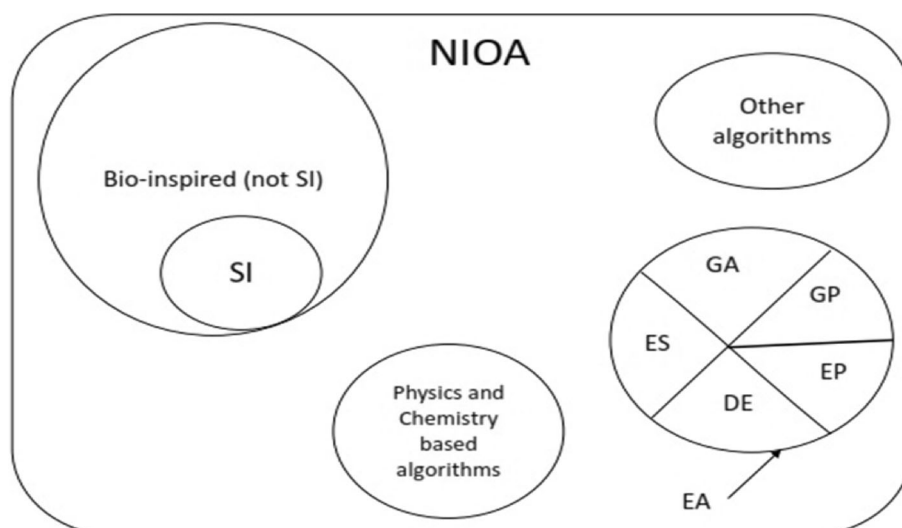


Fig. 2 Similarities and dissimilarities among the classes of EA

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 assist 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:

$$(x_1, x_2, \dots, x_n)^{t+1} = \text{AL}[(x_1, x_2, \dots, x_n)^t]; \dots; (p_1, p_2, \dots, p_m); (rw_1, rw_2, \dots, rw_k)] \quad (3)$$

This expression states that algorithm AL attempts to find better solution $(x_1, x_2, \dots, x_n)^{t+1}$ 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
<i>(a) Bio-inspired (swarm intelligence based) algorithms</i>				
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]
<i>(b) Bio-inspired (not swarm intelligence based) algorithms</i>				
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)	Hernández 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 Khamenechi	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]
<i>Physics and chemistry based algorithms</i>				
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 diffusion 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 Kuczmam	2015	[152]
<i>Other algorithms</i>				
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]
<i>Evolutionary algorithms</i>				
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]

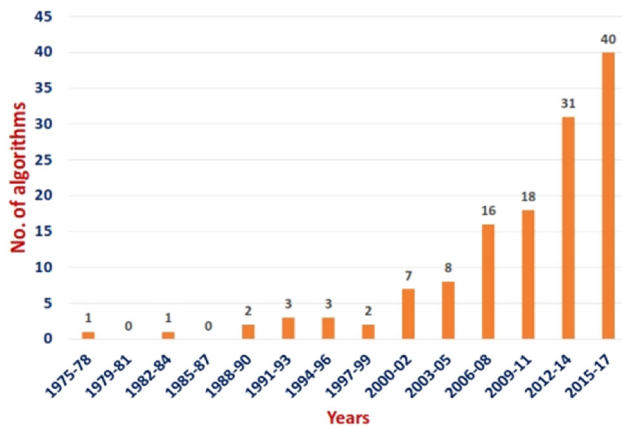


Fig. 3 Year wise development of NIOAs

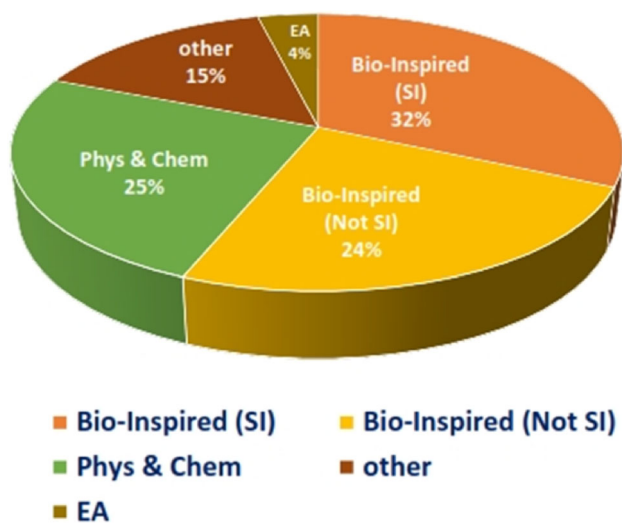


Fig. 4 Majority of different classes of NIOAs

the current iteration t by using the algorithm associated parameters (p_1, p_2, \dots, p_m) and some kind of random numbers $(rw_1, rw_2, \dots, rw_k)$. Several kinds of random number generators can be used to generate $(rw_1, rw_2, \dots, rw_k)$. 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 <i>gbest</i> 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 adaption 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, \dots, 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:

$$G = T_{P_1, P_2, \dots, P_K}(f) \quad (4)$$

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

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

where

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

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 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 classified 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:

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

where $S_K = \{P_1, P_2, \dots, P_K\}$.

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.	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.

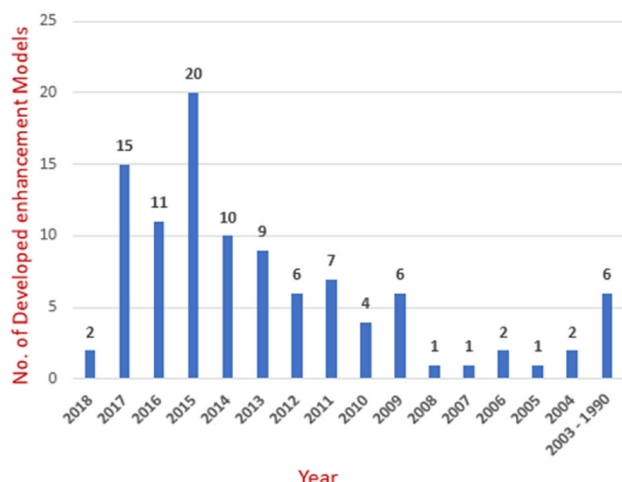


Fig. 5 Year wise development of NIOA based image enhancement models

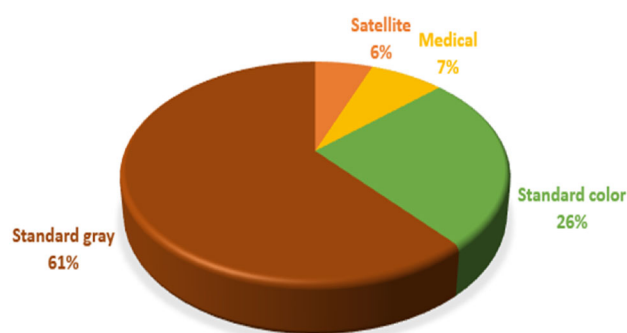


Fig. 6 Application of NIOA based image enhancement model over different image type

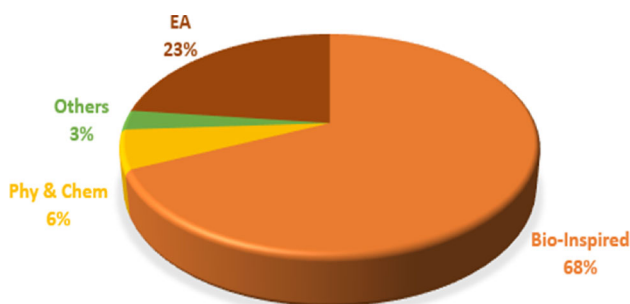


Fig. 7 Class wise application of NIOA in image enhancement domain

- (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 they have no conflict of interest.

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