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The book series is aimed at providing an exchange platform for researchers to summarize the latest research and developments related to nature-inspired computing in the most general sense. It includes analysis of nature-inspired algorithms and techniques, inspiration from natural and biological systems, computational mechanisms and models that imitate them in various fields, and the applications to solve real-world problems in different disciplines. The book series addresses the most recent innovations and developments in nature-inspired computation, algorithms, models and methods, implementation, tools, architectures, frameworks, structures, applications associated with bio-inspired methodologies and other relevant areas.

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Applications of Cuckoo Search Algorithm and its Variants
Evolutionary-based meta-heuristic approaches are effectively applied to solve complicated optimization problems in several real-world applications. One of the successful optimization algorithms is the Cuckoo Search (CS) which becomes an active research area to solve N-dimensional and linear/nonlinear optimization problems using simple mathematical processes. Based on its underpinning in 2009, CS has attracted the attention of various researchers, causing numerous variants of the basic CS with enriched performance. This book highlights the basic concepts of CS algorithm and its foremost variants and their use in solving diverse optimization problems in medical and engineering applications.

This volume entails thirteen chapters providing different CS applications for solving optimization problems. In Chap. 1, Mondal et al. conducted an outstanding, cutting-edge survey focused on the uses of CS and its variants in different digital image processing stages including image enhancement, thresholding, segmentation, feature selection, classification, and compression. Then, in Chap. 2, Campuzano et al. applied the CS for parametric data fitting of characteristic curves of the Van der Waals equation of gases. This study also included a comparative study with polynomial curve fitting and multilayer perceptron neural network, as well as two popular nature-inspired meta-heuristic methods, namely firefly and bat algorithms. In Chap. 3, Ozsoydan et al. introduced the Cuckoo search algorithm with various walks. Novel movement procedures were proposed, including quantum, Brownian, and random walks for CS, which adopts the standard CS form, i.e., Lévy flights. In Chap. 4, Dao et al. implemented a statistical-based CS algorithm for its engineering applications, such as camera-positioning device task. In such an application, CS was used to optimize the design variables, objective functions, and constraints.

In Chap. 5, Kotwal et al. employed the CS algorithm in training a feedforward neural network to solve its inherent problem of being trapped in local minima. This study delineated three different applications of CS-based artificial neural network. In Chap. 6, Carbas and Aydogdu optimized the design of real-sized high-level steel frames using CS. Afterward, in Chap. 7, Singh and Shukla proposed the use of cuckoo search algorithm user interface for parameter optimization of ultrasonic machining process to optimize the required parameters to obtain the desired user
interface profile on the machined surface with less residual damage. In Chap. 8, García-Gutiérrez et al. applied the CS to tune the fuzzy logic controller parameters. In Chap. 9, Das et al. reported different speech processing applications using CS. In Chap. 10, Ocal and Pekcan designed a CS-based back-calculation algorithm for estimating layer properties of full-depth flexible pavements. The performance of the proposed CS-based algorithm was evaluated using synthetically calculated deflections by a finite element-based software and deflection data obtained from the field. Moreover, a comparative study was conducted including the Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Gravitational Search Algorithm (GSA), which concluded the efficiency of the CS compared to these other optimization methods. In Chap. 11, Tutuș et al. applied CS in solving an objective-based design approach of retaining walls, followed by Chap. 12 wherein Altun et al. proposed a hybrid CS and differential evolution algorithms for optimizing the cost of mechanically stabilized earth walls. Finally, in Chap. 13, Maroosi proposed a cuckoo search algorithm inspired from membrane systems, which can concurrently evaluate more than one cost function on parallel devices.

The editor is keen on expressing his gratitude to the contributors for the valuable contributions and the respected referees. An extended gratitude is directed to the members of the Springer team for their support. Am, the editor, wishes this book entails advanced, valuable research on Cuckoo search and its variants to solve diverse optimization engineering problems in real-world clinical applications.

Kolkata, India

Nilanjan Dey, Ph.D.
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Chapter 1
Cuckoo Search and Its Variants in Digital Image Processing: A Comprehensive Review

Atreyee Mondal, Nilanjan Dey, and Amira S. Ashour

1 Introduction

In computer vision, image processing refers to the analysis and manipulation of digital images to improve their quality [1]. Upgrading the visual appearance of the image and extracting the significant information from images are considered the main tasks of the image processing [2]. Image processing is a subset of the digital signal processing, where the input parameter can be an image or a sequence of images in a video, while the output may be some features related to the image or an image frame [3]. Image processing has a wide range of techniques, such as image enhancement, image denoising, image clustering, image segmentation, feature extraction, feature selection, image classification, and image compression, [4]. In recent years, image processing becomes more challenging due to the huge amount of the complicated, noisy images from the different sources in a variety of applications, which requires minimal computational cost/time procedures and higher accuracy [5]. Therefore, and along with the different parameters in each image processing stage which require fine-tuning and accurate selection of their values, optimization algorithms become essential to resolve such challenges in a time efficient manner.

Optimization algorithms perform competently well to effectively reduce the computational cost, increase the performance, and minimize energy consumption [6, 7].
In image processing, the optimization problem arises to check the reliability of the algorithm by considering different components, such as the formulation of dependency between parameters [8]. The main objective of optimization algorithms is to find ideal, feasible, and optimal solution for the problem statement. To obtain such solutions, the algorithms initially incorporate a random solution vector and begin to traverse the entire search space and move to better approach in each step which ultimately results in the best solution in less time [9–12]. However, in real world, implementing a single feasible solution is a challenging task.

Typically, metaheuristics optimization algorithms are powerful tools in image processing techniques, such as image enhancement, and image denoising [13, 14] methods for pre-process digital images. After pre-processing, the segmentation process is carried out [15].

Over the past few decades, various optimization algorithms are developed from some inspiring features of nature, including genetic algorithm [16, 17], which is developed from Darwin’s survival of fittest theory, particle swarm optimization algorithm (PSO) [18], which was inspired by swarm movements. Furthermore, ant colony optimization [19] influenced by the ant behaviour. Apart from these, bat algorithm [20], flower pollination algorithm [21], firefly algorithm [22], shuffled frog leaping algorithm [23], bacterial foraging optimization algorithm [24], artificial bee colony algorithm [25], and artificial fish swarm algorithm [26], which are influenced by natural phenomena and utilize different degrees of exploration and exploitation for searching purpose.

In this study, a comprehensive review of one of such nature-inspired metaheuristic optimization algorithm, namely, cuckoo search (CS) is presented. The CS algorithm is inspired by the obligate brood parasitic strategy in combination with Lévy flight behaviour of cuckoo bird. Relevant researches represent that CS algorithm works are efficient in different digital image processing stages, such as pre-processing, segmentation, feature selection, classification, and compression. A detailed discussion of the performance of CS and its variants in several applications is introduced in this work.

The rest of this study is carried out as follows. The classical CS algorithm and its variants as well as hybrids are discussed in Sect. 2. In Sects. 3 through 7, different image processing methods using CS are concisely reviewed. In Sect. 8, various applications are collectively highlighted. Finally, Sect. 9 depicts the conclusion.

2 Metaheuristic Algorithms in Digital Image Processing

2.1 Cuckoo Search Algorithm

Cuckoo search algorithm (CS) is considered a nature-inspired metaheuristic structural optimization algorithm introduced by Xin-she Yang and Suash Deb in the year 2009 [27]. The algorithm was induced by obligate brood parasitic strategy of most
of the cuckoo species in composition with the Lévy flight characteristics of some species. The reproduction characteristics of cuckoo bird species follow the typical obligate brood parasitism, where they lay their eggs to exploit a host bird’s nest. Often the host bird has different species other than cuckoo. Very few species of cuckoo like guira, Smooth-billed Ani, and the Greater Ani nests in their own community and thus considered as non-parasitic species. These rare cuckoo species practices cooperative breeding behaviour, where more than one female cuckoo lays eggs in the communal nests [28]. The adults remove the other cuckoo-chicks to strengthen the possibility of incubating their own chicks when other members are away from nest for feeding [29].

Apart from these few species most of the cuckoo species perform obligate brood parasitic behaviour by breeding in the host bird nests. Sometimes the host bird simply leaves its nest or throw the eggs out of their nests if they discover the egg as an alien egg. To increase the reproduction probability, some special female cuckoo species mimicry their eggs, which are alike in colour and pattern as the host bird. Moreover, the specialization in breeding time is also notable because in most of the cases, the female cuckoo selects those nests where the host bird recently came up with its own eggs [30]. Several relevant studies show that the cuckoo chick hatch a little prior to the eggs of host bird and can also imitate the sound of host chicks to increase the food consuming probability from the host bird [31].

Some species search for food in an arbitrary or relatively random way, where the probability of the next random movement path direction can be formulated mathematically [32]. The flight behaviour of different species indicates the classical Lévy flight characteristics [33–35]. In CS algorithm, a cuckoo searches host nest using Lévy flights, which was titled by the French mathematician Paul Lévy representing the typical strategy of random walk designated by its step length which fulfils a power law distribution [36]. Relevant researches depicted that the Lévy flights have also been perceived among hunting strategy of albatross species and fruit flies. It maximizes the efficiency of resources in uncertain environment [37]. The traditional CS algorithm follows three idealizations, namely,

i. Each female cuckoo bird breed one egg at once and selects an arbitrary host nest to dump it;

ii. The prime nests which have the best standard of eggs are carried over to the descendants; and

iii. The amount of accessible host nests is constant, and the cuckoo egg being recognized by the host bird is with a probability $p_a \in (0, 1)$.

If $p_a \neq 0$, the host bird can either eject the alien egg or leave its nest and form an entirely fresh one in another locality. For transparency, this end presumption can be approached by a fraction $p_a$ of the $n$ nests that are substituted by fresh nests.

In maximization problem, the fitness of a solution varies in direct proportion with objective function value. The mathematical form of maximization problem is given by [38]:

$$\min(f(x)) = \max(-f(x))$$

(1)
In this case, the following assumption can be considered, where each egg in a host nest is a solution and cuckoo egg depicts a new solution. Also, for ease, it is presumed that there is only a single solution in host nest. The objective is to substitute comparatively poor solution with preferable new solutions (cuckoo egg). This algorithm becomes more complex when each host nest has a set of solutions, i.e. multiple eggs.

Based on the above-idealized rules, the pseudo-code of the original CS algorithm can be summarized as follows:

**Classical CS Algorithm:**

Input: Population of nests  
Output: Best Solution and its corresponding value  

Begin  
Consider a population of n host nests $x_j$, where $j=1,2,3...,n$  
m=0  
while (m<MaxGeneration)  
  Choose an arbitrary cuckoo via Lévy flights  
  Compute its fitness $F_j = f(x_j)$  
  Get a random host nest x amongst n host nests (say k)  
  $F_k = f(x_k)$  
  if ($F_j > F_k$)  
    Replace k with new solution (cuckoo egg)  
  end if  
  Leave a fraction $p_a$ of the substandard nests and new nests are construct at new locality using Lévy flights  
  Analyse fitness of new nests/solutions  
  Rank all solutions to find the best solution  
  Pass the best solution to the next generation  
end while  
Visualization  

end

In CS, the lévy flight can be used for local and global exploration. The former used to improve the best solution via random walks directly, whereas the latter uses lévy flight strategy to maintain diversity of the population. The generation of new solution $x_{m+1}^m$ for a randomly selected cuckoo $i$ is performed via lévy flight.

$$x_{i}^{m+1} = x_{i}^{m} + \alpha \oplus Le^{'}vy(\lambda) \quad (2)$$

where $\alpha > 0$ representing the step size, and $Le^{'}vy(\lambda)$ denotes the characteristic scale as $\alpha = O(1)$ in maximum cases.

The lévy distribution function with infinite mean and variance for random step length evaluation in random walk of lévy flight is depicted using the following expression:
where \( \lambda \in [1,3] \). In this context, the sequential jumps of a cuckoo bird create a random walk behaviour which follows the power law distribution with a dense tail [39].

2.2 CS Variants and Hybrids

There are numerous variants of CS appear in the models proposed by many researchers after the invention of the original CS algorithm, such as discrete CS [40], binary CS, modified CS [41, 42], neural-based CS [43], gaussian distribution-based CS [44], modified adaptive CS [45], quantum inspired CS [46], and parallelised CS [47]. In this study, the relevant models are concisely highlighted.

Binary Cuckoo Search (BCS)
The binary cuckoo search algorithm is an extended version of classical cuckoo search algorithm, which is broadly used for feature selection. Feature selection is the mechanism by which the best subset of features can be found for solving classification or clustering of digital image in computer vision [48, 49]. Hence, feature selection problem is treated as a discrete binary problem and designed as \( n \)-dimensional Boolean lattice problem [50] in which the solutions are updated across the corners of a hypercube on a contrary of original CS where solutions are updated in a search space in a continuous domain. The features are either selected or rejected is decided using a binary vector and are represented by 0 or 1 [51]. To measure the quality of a solution, a binary vector is generated converting the dimension of the solution to binary values represented as follows:

\[
y_i^j(t') = \begin{cases} 
0 & \text{if } x_i^j(t') < \sigma \\
1 & \text{if } x_i^j(t') \geq \sigma 
\end{cases}
\]

where \( x_i^j(t') \) denotes the value of \( i \)th egg at time \( t' \) for the \( j \)th nest, \( y_i^j(t') \) stands for binary vector at \( j \)th nest at time \( t' \), and for \( t' = 0 \), which represents the primary solution. Here, in the above equation, \( \sigma \in (0, 1) \), depicts the Boolean boundary.

Improved Cuckoo Search (ICS)
The traditional CS algorithm is improved by some parameters and different improved versions evolved. These are used to serve different purposes, such as training feedforward neural network and solving unconstrained global optimization problem.

To find the locally improved solution, the parameters \( p_a \) and \( \lambda \) are used and for global solution, it uses the value of \( \alpha \) [52]. Unlike classical CS, the parameters \( p_a \) and \( \alpha \) value changes dynamically with the number of new generations [53]. The following Eqs. (5–7) satisfy the above statement:
\[ p_a(c) = p_a(\text{max}) - \frac{c}{n} \left( p_a(\text{max}) - p_a(\text{min}) \right) \]  

(5)

\[ \alpha(c) = \alpha_{\text{max}} \times \exp(b \cdot c) \]  

(6)

\[ b = \frac{1}{n} \ln \left( \frac{\alpha_{\text{min}}}{\alpha_{\text{max}}} \right) \]  

(7)

where \( n \) represents the total number of iterations and \( c \) represents the current one.

An improved cuckoo search (ICS) method with increased efficiency, which is used to train feedforward neural networks and thereby solving classification problems, was proposed in [54]. A constructive heuristic called NEH [55] is incorporated with traditional CS to find optimal solution and used for task scheduling, reported in [56].

For a set of optimization problems, sometimes CS cannot reach to the desired solution. To overcome this deficiency CS is hybridized with some other optimization algorithms or machine learning models, applied in nearly each element of CS [57]. For example, hybrid CS/GA [58, 59] and hybrid CS [46] are the models proposed in the aforementioned context.

### 3 Image Pre-processing

Image pre-processing includes image enhancement and denoising. Image enhancement is the process of sharpening digital image features, such as edge, and contrast for meaningful representation for further display and image analysis [60]. Image enhancement improves the intrinsic information as well as the dynamic range of features in the image for easier detection [61]. To improve the perception of a digital image, two different methods are used, namely, spatial domain techniques and frequency domain techniques [62]. The former one directly works on pixels, whereas the latter deals with Fourier transform of a digital image [63]. Transform function optimization is non-linear in nature and is used to stretch the dark/blur grayscale image. Some gray level transformation includes point transformation, linear transformation, logarithmic transformation, and power-low transformation [64, 65].

Generally, for efficient image enhancement, specific criteria are considered. To obtain the objective function for optimization, selection of the standard of image enhancement associated with quality function is important [66]. The quality function describes the image features in details. The performance measurement parameters reported in [67] are entropy, sum of the edge intensity, and the number of edge pixels. The objective function \( O(t') \) can be formulated as follows [68]:

\[ O(t') = \ln(E(I_e)) \times \left( \frac{n_{\text{edges}}(I_e)}{(i \times j)} \right) \times H(t') \]  

(8)
where \( O(t') \) represents the fitness/quality value of the enhanced image, \( E(I_e) \) denotes the intensity of the pixels of image \( I_e \), and \( n_{\text{edges}}(I_e) \) is the number of edge pixels or edges with intensity above threshold in \( I_e \). \( H(t') \) represents the entropy of the enhanced image \( t' \) and \( i, j \) denote the rows and columns of the image, respectively.

The image enhancement has wide application domains, such as for medical images and satellite images using CS. In [69], an optimal parameter estimation for log transformation was addressed. Here, computed tomography visual enhancement model was proposed via CS optimization algorithm. A contrast-based image enhancement approach is proposed in [70] using CS for quality advancement of low contrast satellite images. In addition, image denoising refers to the process in which an image can be reconstructed by removing the unwanted noise [71]. This process is very useful for medical imaging applications to separate original image from the noisy one [72, 73]. A hybrid filter is proposed in [74] via CS, where CS is pointed to be the most appropriate and effective optimization algorithm.

4 Image Segmentation

In computer vision, image segmentation is referred to as the process of partitioning digital images into multiple segments on the basis of features, like colour, texture, patterns, and shapes to analyse an image in easier and humanly way [75]. Image segmentation technique can be broadly categorized into threshold-based, region-based, and edge-based [76, 77].

Threshold-based Techniques

Thresholding methodologies are most frequently used to segment images [78]. Threshold is used to determine intensity values of the grayscale images for classifying distinctly into different clusters [79]. The thresholding can be further subdivided into bi-level and multilevel thresholding [80]. In Bi-level thresholding technique, the input image is subdivided into background and foreground pixels and can be represented using the below formulations [81]:

\[
A_0 = f(x, y) \in I \mid 0 \leq f(x, y) \leq t' - 1 \\
A_1 = f(x, y) \in I \mid t' \leq f(x, y) \leq L' - 1
\]

where \( f(x, y) \) is the corresponding intensity value of the pixel, and \( I \) represent the sample image needs to be processed.

Multilevel thresholding techniques differentiate the object of interest from the image and also used for colour images, where the value of R, G, B are distinctly processed with different gray levels [82]. The following mathematical formulations represent the multilevel thresholding:
\[ A_0 = f(x, y) \in I | 0 \leq f(x, y) \leq t'_1 - 1 \]
\[ A_1 = f(x, y) \in I | t'_1 \leq f(x, y) \leq t'_2 - 1 \]
\[ A_i = f(x, y) \in I | t'_i \leq f(x, y) \leq t'_{i+1} - 1 \]
\[ A_n = f(x, y) \in I | t'_n \leq f(x, y) \leq L' - 1 \] (10)

where \( f(x, y) \) is the corresponding intensity value of the pixel, \( I \) represent the sample image needs to be processed, and \( t'_i = 1, 2, \ldots, n \) (where \( n = \text{total number of threshold values} \) [83]).

To maximize the objective function, different techniques can be used, such as Kapur’s entropy, and Otsu’s/Tsallis’s entropy [84]. Generally, to search optimal threshold, the time complexity of the classical methods becomes higher [85]. In [86], a multilevel threshold-based CS technique was proposed using minimum cross entropy. A region-based CS algorithm is proposed in [87] for colour image segmentation. An adaptive CS algorithm for image segmentation is reported in [88]. In [89, 90], a multilevel thresholding technique is comparatively studied using optimization algorithms.

**Otsu’s between class variance method**

Otsu’s is a nonparametric segmentation method which increases the inner class variance and reduces the within class variance of pixels [91–93]. It can be represented as a summation of the above two variances in Eq. (10):

\[ \sigma^2_b(T') = B_1(T') \sigma^2_1(T') + B_2(T') \sigma^2_2(T') \] (11)

where \( \sigma^2_1(T') \) and \( \sigma^2_2(T') \) are two class variance and \( B_1(T') \) and \( B_2(T') \) are the class segmentation probabilities by \( T' \) and are calculated as follows:

\[ B_1(T') = \sum_{i=0}^{T'-1} p(i) \]
\[ B_2(T') = \sum_{i=T'}^{H-1} p(i) \] (12)

The main disadvantage of Otsu’s method is the long searching time, but it can be reduced and become time efficient using metaheuristic algorithms. A modified CS is proposed in [94] with thresholding techniques and turned out to be a time efficient method. To maximize the inner class variance, the following formula is used:

\[ \rho^2_{\text{max}} = \sigma^2 - \sigma^2_b(T') \]
\[ = B_1(\mu_1 - \mu_i)^2 + B_2(\mu_2 - \mu_i)^2 \]
\[ = B_1(T') B_2(T') [\mu_1(T') - \mu_2(T')]^2 \] (13)
The $\mu_{1,2,1}(T')$ represents the mean of classes and can be formulated as

$$\mu_1(T') = \frac{\sum_{i=0}^{T'-1} i p(i)}{B_1(T')}$$  \hspace{1cm} (14)$$

$$\mu_2(T') = \frac{\sum_{i=T'}^{H'-1} i p(i)}{B_2(T')}$$  \hspace{1cm} (15)$$

$$\mu_t(T') = \sum_{i=0}^{H'-1} i p(i)$$  \hspace{1cm} (16)$$

The optimal threshold can be calculated by computing maximum value of $\rho_{\text{max}}^2(T')$.

## 5 Image Compression

Image compression is a technique of data compression used to minimize the storage and transmission cost of digital image [95]. There are loosely two types of image compression, namely, lossless and lossy compression. Vector quantization (VQ) is turned out to be an efficient tool for lossy image compression. The objective of VQ is to search the closet codebook by training test images [96]. Linde Buzo Gray (LBG) [97] algorithm is the most frequently used VQ method which designs a local optimal codebook for image compression. However, it cannot find the global best solution [98]. VQ is one of the block coding methodologies for image compression [99]. The prominent part of VQ design is codebook implementation [100]. Assume the original image of size $s \times s$ is quantized and branched in $S_a \left( \frac{s}{K} \times \frac{s}{K} \right)$ blocks each of size $K \times K$ pixels. Each branch is represented as $A_j$ where $j$ ranges from 1 to $S_a$. Total number of codewords in codebook is $S_c$. The minimum Euclidian distance is calculated between vector and the codewords based on which every subgroup of images is approximated. The encoded results are named as index table. The distortion $\beta$ between training vectors and codebook can be represented as

$$\beta = \frac{1}{S_c} \sum_{i=1}^{S_c} \sum_{j=1}^{S_a} v_{ji} \times |A_j - C_i|$$  \hspace{1cm} (17)$$

Using the following constraints:

$$\beta = \sum_{i=1}^{S_c} v_{ji} = 1$$  \hspace{1cm} (18)$$

where $v_{ji} = 1$ if $A_j$ is in the $i$th cluster, else it becomes 0.
In [101], the CS algorithm has been used to compress medical image based on wavelet particles. A hybrid CS algorithm is proposed in [102] for image compression using vector quantization. In [96], a modified CS optimization was proposed for image compression based on VQ.

6 Feature Selection

Feature selection is the process which aims to extract the most discriminative subset of features from an image for easier classification [103, 104]. There are several feature selection mechanisms, most of them generally eliminates variables in a step-by-step manner [105]. For example, sequential floating forward selection (SFFS) [106], which has a forward step for insertion and a backward step for deletion to partially ignore local minima [107]. A direct sequential feature selection mechanism selects the most excellent feature from all the available features [108]. In sequential backward selection (SBS) mechanism, the algorithm begins by selecting the fully complete group of features and removes one variable an instance such that the predictor performance will be least affected [109, 110]. However, the sequential feature selection (SFS), SFFS methods suffer from nesting effect. To solve this limitation, an adaptive version of SFFS was proposed in [111, 112], which developed a better subset than SFFS although it is dependent on the objective function and data distribution.

The major disadvantage of sequential feature selection techniques is during the starting phase of the searching process, it can lock at a local minimum. To avoid this problem, such techniques can be replaced by various optimization algorithms such as particle swarm optimization (PSO) algorithm [113, 114], genetic algorithms [115, 116], ant colony optimization (ACO) algorithm [117, 118], firefly algorithm [119, 120], and cuckoo search algorithm. The above population-based optimization algorithms can be used for functional optimization in high-dimensional space.

A hybrid CS is proposed in [121] for feature selection, where an objective function is formulated to compute fitness depending upon the classification quality and the total number of features. The objective function \( \text{Fit}(R') \) is calculated as follows:

\[
\text{Fit}(R') = n_1 \times \theta_{Z'}(V) + n_2 \times \left( 1 - \frac{|R'|}{|Z'|} \right) 
\]

where \( Z' \) is the total number of selected features and \( R' \) is the features selected from the set of features. Here, \( n_1 \) and \( n_2 \) represent the relative quality between \( |R'| \) and classification performance, respectively. A modified BCS method is proposed in [121] for feature selection.
7 Image Classification

Image classification refers to labelling of a digital image into different categories based on features of the image [122]. In [123], an extreme learning machine (ELM) was trained using improved version of CS algorithm and further utilized in the field of medical image classification. Some parameters of ELM, such as regularization coefficient, Gaussian kernel, and hidden number of neurons were minimized via CS. In this context, classification accuracy is treated as objective function. A framework has been presented in [124] for band selection in hyperspectral image classification using binary CS. Here, the band selection is treated as a combinational problem and the objective function is used to reduce the error probability during classification.

8 Application Areas

The original cuckoo search algorithm and its variants have a wide range of application domains. This section mainly focuses on application of cuckoo search in the field of data fusion, data clustering, flood forecasting, multilevel image thresholding, groundwater expedition, face recognition, travelling salesman problem, task scheduling, business optimization, n-queens puzzle problem, and computer games. Relevant researches in this context have showed that cuckoo search is one of the simplest metaheuristic algorithms too because of having a single parameter $p_a$. Also, the global search capacity of this optimization algorithm is notable.

Some prominent applications of CS are briefly discussed as follows. Nurse scheduling algorithm [125] is developed using CS and is widely used in healthcare around the world to maintain nurse management system. A modified CS is used to solve effective non-linear problems, like mesh generation as reported in [42]. In some cases, CS outperforms over most of the well-known structural optimization algorithms, for example, engineering design such as spring design or welded beam design [39, 126]. In [127], CS provided the optimal solution for designing embedded systems. CS has also been used for designing steel frames as reported in [128]. In [46], a new quantum inspired CS based on quantum computing concepts like quantification, quantum bit representation, disruption, and quantum mutation were presented. The proposed algorithm increases the efficacy by minimizing the population size and number of iterations to reach the optimal solution. Quantum inspired CS has also been effectively used to solve combinational optimization problems such as 1-D bin packing problem (BPP) [129]. NP hard problems such as symmetric travelling salesman problem, knapsack problem can be solved by adapting an improved cuckoo search algorithm, reported in [130, 131]. In [132], a three-step polynomial metamodel is proposed to optimize OP-AMP using CS. An enhanced scatter search algorithm is proposed in [133] by adapting modified CS. This is generally used to solve various continuous as well as combinational optimization problems.
The most significant applications of CS include training neural networks and handle reliability optimization problem, addressed in [53, 54]. A multiobjective CS (MOCS) was developed in [134] to implement engineering applications [135]. A feature selection algorithm based on CS was proposed in [136] for efficient face recognition. A comparison between PSO and CS also done in [136], where CS was turned out to be a better performing algorithm in identification of face. Wireless sensor network was introduced as an emerging application of CS, reported in [137].

Apart from these CS also performed competently to solve six-bar double dwell linkage problem [138], DG allocation problem [139], business optimization [140], query optimisation [141], sheet nesting problem [142], machining parameter selection [143], automated software testing problem [144], UCAV path planning [145], manufacturing optimization problem [146], web service composition problem [147], Groundwater expedition [148], ontology matching [149], planar graph colouring [150], job scheduling problem [151], and flood forecasting [152]. Additionally, it is recommended to compare the performance of the CS with other optimization methods, such as the GA, PSO, ABC, and FFA, which have engaged in different image processing applications [153–160].

9 Conclusion

Image processing and pattern recognition have a significant role in vision systems, medical applications, remote sensing, and more other applications. A typical image processing system includes successive operations/processes in different levels, namely, low-level using filtering procedures, middle-level using edge detection and segmentation methods, and high-level using extraction techniques and classification methods. Accordingly, parameters tuning is considered the most common difficulty which obstacle the design and performance of these systems. Parameter optimization is a complicated, nontrivial, and iterative challenging process to determine the preeminent outputs by fine-tuning the values of such parameters.

Nature-inspired optimization including swarm intelligence techniques are extensively laboured in different image enhancement, segmentation, clustering, features selection, and classification processes to determine the optimal values of parameters by maximizing or minimizing appropriate objective functions. Accordingly, several metaheuristic-based algorithms, such as ACO, GA, PSO, and CS established their efficiency in different optimization problems. The iterative process of the optimization algorithms is a bottleneck in the image processing domain.

In this chapter, the CS optimization algorithm was introduced in detail along with its variety in the image processing stages to automatically optimize the inherent parameters, which affect the performance of these stages. The general framework and the concept of the CS with its variety were introduced in this chapter as a milestone for any further use of the CS in the different applications. Different studies and applications based on the CS algorithm were reported. Each experiment entails
variables and entries, such as filter size, threshold level, number of clusters, and number of classes. Such variables may be controlled or uncontainable.

The CS algorithm is one of the efficient metaheuristic methods inspired by the activities of cuckoo species, including brood parasites along with the features of the Lévy flights, including fruit flies and birds. It is based on three main operations/rules in a simple manner. The reported studies established that the CS is a powerful optimization algorithm in the image processing applications due to its simplicity and efficient time-consuming ability.

References

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