ENHANCED CUCKOO SEARCH ALGORITHM WITH METAHEURISTIC COMPONENTS FOR EXTRACTING THE MAXIMA OF THE ORIENTATION DISTRIBUTION FUNCTION

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UNIVERSITI SAINS MALAYSIA

2018

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by

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Thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosphy

June 2018

ACKNOWLEDGEMENT

First of all, I would like to express my gratitude to Almighty Allah for giving me the physical and mental strength throughout my research study. I would like to express sincere gratitude to my supervisor Professor Ahamad Tajudin Khader for his insightful guidance throughout the entire period of my research. I am also grateful to Dr. Makhlouf Laouchedi from the University of science and technology houari boumdiene Algeria and Center hospital of the army (Algeria) for his help and useful discussion in the Medical field. As well I really appreciate the effort made by Dr. Iman Aganj from Harvard Medical School (USA) for his knowledgeable suggestions and valuable advice on the practical side. Also, I'd like to thank Ms. Suzana Binti Mat Isa from the Advanced Medical and Dental Institute (AMDI/USM) for her kindness in data acquisition.

Most of all, I would like to express my deepest appreciation to my beloved parents who always encouraged me to go ahead with my study. All thanks to my father and my dearest mother for your prayers and support. I'm much grateful for my brothers and sisters for all the unconditional love, support, and encouragement.

Last but not least, I would like to express my sincere and heartfelt thanks to my dear friends inside and outside Malaysia who supported me during my research study.

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LIST OF ABBREVIATIONS

ACSA-ODF	Adaptive Cuckoo Search Algorithm for Orientation Distribution Function
AMDI	Advanced Medical and Dental Institute
ABC	artificial bee colony
ADC	apparent diffusion coefficient
ASSF	Antidotally Symmetric Spherical Function
BA	Bat Algorithm
BCS	binary cuckoo search
BCSA	Basic Cuckoo Search Algorithm
BET	brain extraction tool
CSA	Cuckoo Search Algorithm
CSBA	Hybridization MCSA with Bat algorithm
CSBA-ODF	CSBA for Orientation Distribution Function
CSBAHC	Hybridization CSBA with Hill Climbing
CSAHC-ODF	CSBAHC for Orientation Distribution Function
DE	differential evolution
DTI	Diffusion Tensor Imaging
DSI	Diffusion Spectrum Imaging
DWI	Diffusion Weighted Imaging

DICOM	Digital Imaging and Communications in Medicine
DSCA	discrete cuckoo search
EAs	evolutionary algorithms
FA	firefly algorithm
FRT	Funk-Radon transform
FA	Fractional Anisotropy
GA	Genetic Algorithm
GP	genetic programming
HS	Harmony Search
HC	Hill Climbing
HP	homogeneous polynomial
ICSA	improved CSA
HARDI	High Angular Resolution Diffusion Imaging
IPPT	Institut Perubatan dan Pergigian Termaju
MO-RAGE	magnetization-prepared rapid gradientecho
MRI	Magnetic Resonance Imaging
MD	Mean Deviation
MCSA	Modified Cuckoo Search Algorithm
MCSA-ODF	Modified Cuckoo Search Algorithm for Orientation Distribution Function
NIfTI	Neuroimaging Informatics Technology Initiative

ODF Orientation Distribution Function

PSO Particle Swarm Optimization

PAS persistent angular structure

PDF Probability Density Function

PGSE Pulsed Gradient Spin Echo

QBI Q Ball Imaging

QC Quantum computing

RBF Radial Basis Function

RSSH real symmetric spherical harmonics

SA simulated annealing

SNR signal to noise ratio

SH spherical harmonic

SMES super conducting magnetic energy storage

ST symmetric tensor

TS tabu search

t tournament size

TSE Turbo Spin Echo

ALGORITMA CARIAN CUCKOO YANG DITINGKATKAN DENGAN KOMPONEN METAHEURISTIK UNTUK MENGESTRAK MAKSIMA KEFUNGSIAN AGIHAN ORIENTASI

ABSTRAK

The Diffusion-Weighted Magnetic Resonance Imaging (DW-MRI) atau Pengimejan Resonan Magnetik yang Dipengaruhi Difusi adalah satu kaedah yang baik untuk pengkajian bukan-invasif perkaitan anatomi dalam otak manusia. Data mentah yang diperolehi dari pengimbas MRI mungkin tidak boleh digunakan secara langsung oleh pakar. Oleh itu, kaedah-kaedah baru diperlukan untuk membuat perwakilan data yang wajar untuk mengestrak maklumat yang diperlukan daripadanya.Perwakilan awal data MRI adalah kumpulan gentian yang terbesar. Gentian-gentian ini mengandungi lintasan gentian dalam bentuk pukal, yang menyambungkan kawasan-kawasan otak yang berfungsi sebagai satu jaringan komplek saluran gentian neural. Pengimejan bebola-Q (QBI) adalah satu teknik Difusi MRI yang terbukti berjaya dalam menyelesaikan orientasi gentian pelbagai intravoksel dalam MRI (i.e., lintasan gentian) berdasarkan komputasi piawai Kefungsian Agihan Orientasi atau Orientation Distribution Function (ODF), iaitu satu fungsi bersfera 3- dimensi yang didapati mampu mengesan orientasi gentian dominan dalam volum piksel sedia ada (voksel).Disertasi ini membentangkan satu kaedah baru menyelesaikan masalah ODF melalui pen-gadaptasian salah satu algoritma metaheuristik iaitu Cuckoo Search Algorithm (CSA) atauAlgoritma Carian Cuckoo untuk ODF. Adaptasi tersebut melibatkan penyediaan data sintetik untuk ujian. Keputusannya berada dalam julat kajian terdahulu dan lebih baik berbanding den-gan

Algoritma Carian Cuckoo untuk ODF. Adaptasi tersebut melibatkan penyediaan data sintetik untuk ujian. Keputusannya berada dalam julat kajian terdahulu dan lebih baik berbanding dengan algoritma-algoritma lain. Namun demikian, beberapa kekurangan dalam kadar pemusatan dan eksploitasi tempatan ditentukan dan dkendalikan dengan cara mempertingkatkannya dengan komponen-komponen metaheuristik. Tiga versi peningkatan berturut-turut disarankan iaitu penambahbaikan berperingkat melalui versi terdahulu: (i) Algoritma Carian Cuckoo yang telah diubahsuai (MCSA); (ii) Menghibridkan MCSA dengan komponen algoritma bat (CSBA), dan (iii) Menghibridkan CSBA dengan pendakian bukit(CSAHC). Eksperimen versi-versi ini berjaya melepasi dua peringkat: Peringkat pertama, dibandingkan dengan 5 kaedah lain menggunakan tigabelas fungsi penanda aras dari pelbagai kategori. Tujuannya ialah menguji setiap versi sebelum menggunakannya untuk ODF. Peringkat kedua ialah membandingkannya dengan 5 kaedah lain menggunakan data sintetik. Tujuannya ialah untuk memilih versi terbaik dalam usaha untuk mengaplikasikannya kepada data otak manusia. Keputusannya menunjukkan bahwa setiap versi telah bertambah baik selepas versi-versi terdahulu. CSAHC-ODF adalah ODF yang dibina semula dengan lebih tajam dan lebih tepat dan mengestrak maksima dalam kawasan pukal gentian yang bertemu, atau lebih tepat dpanggil.

ENHANCED CUCKOO SEARCH ALGORITHM WITH METAHEURISTIC COMPONENTS FOR EXTRACTING THE MAXIMA OF THE ORIENTATION DISTRIBUTION FUNCTION

ABSTRACT

The Diffusion-Weighted Magnetic Resonance Imaging(DW-MRI) is a promising method for non-invasive investigation of anatomical connectivity in the human brain. The raw data acquired from the MRI scanner may not be directly usable by the specialists. Therefore, new methods are required to make more reasonable representations of the data to extract the required information from them. The initial representation of the MRI data is the huge groups of fibers. These fibers contain fiber crossing bundles, which link the functional brain areas all together as a complex net-work of neural fiber tracts. Q-ball imaging (QBI) is a Diffusion MRI reconstruction technique which has been proven very successful in resolving multiple intravoxel fiber orientations in MRI (i.e., fiber crossing) based on the standard computation of the Orientation Distribution Function (ODF), which is a 3- Dimension spherical function founded to detect the dominant fiber orientations in the underlying volume of a pixel (voxel). This dissertation presents a new method to solve ODF problem through adapting one of the metaheuristic algorithms, namely, Cuckoo Search Algorithm (CSA) for the ODF. The adaptation involved preparing the synthetic data for testing. The results were within the range of previous work and better comparing the other algorithms. However, some shortcomings in the convergence rate and local exploitation were determined and addressed by enhancing with known metaheuristic components. Three successive enhancement versions are proposed

tions of various categories. This is to test each version before using it for the ODF. The second step compares against five other methods using synthetic data. The ODFs reconstructed by CSAHC-ODF are sharper and more accurate ODFs than the original image and extracts more accurate maxima.

CHAPTER 1

INTRODUCTION

1.1 Background

The brain is the most complex organ in the human body because it consists of about 100 billion neurons and one million billion (10^{15}) interconnections (Azevedo et al., 2009). This organ is the control for the sensorimotor such as walking and breathing, cognitive functions such as talking, reasoning, memory and more complex functions such as emotions and feelings. The brain is also a subject of many diseases that need surgery, which could result in either deterioration of the cited functions or even in permanent disability. Medical imaging, especially Magnetic Resonance Imaging (MRI), helps mapping the anatomical and functional aspects of the brain, considered as the substratum of the different functions. In the first part of this section, a brief overview of the diffusion MRI is presented, followed by an overview of the Cuckoo Search Algorithm (CSA). The justifications for using the CSA to solve the ODF problem are given at the end of this section.

1.1.1 Diffusion MRI

The central nervous system is made up of neurones. A neurone is constituted of two types of tissue, namely the gray matter where cell bodies of neurons reside in the brain and spinal cord, and the axone forming the white matter, which are extensions of neural cells as shown in Figure 1.1. Integration of the neural processes in the human brain is realized through interconnections that exist between different neural centers (cortical centers). This connectivity is altered by some pathologies or trauma, resulting in deterioration of sensorimotor and cognitive capabilities. For this reason, it is of high importance to probe this connectivity and evaluate its integrity.

Diffusion MRI measures the diffusion of water molecules along a set of directions (Le Bihan et al., 1986). Diffusion MRI is a noninvasive method based on the Brownian (random) motion of water molecules constrained by neuronal tissues in vivo. During the early 2000s, various research groups have been proposed to build structural connection matrices from diffusion MRI fiber tracking through employing different diffusion acquisition techniques (Thottakara et al., 2006; Iturria-Medina et al., 2007; Gong et al., 2009).

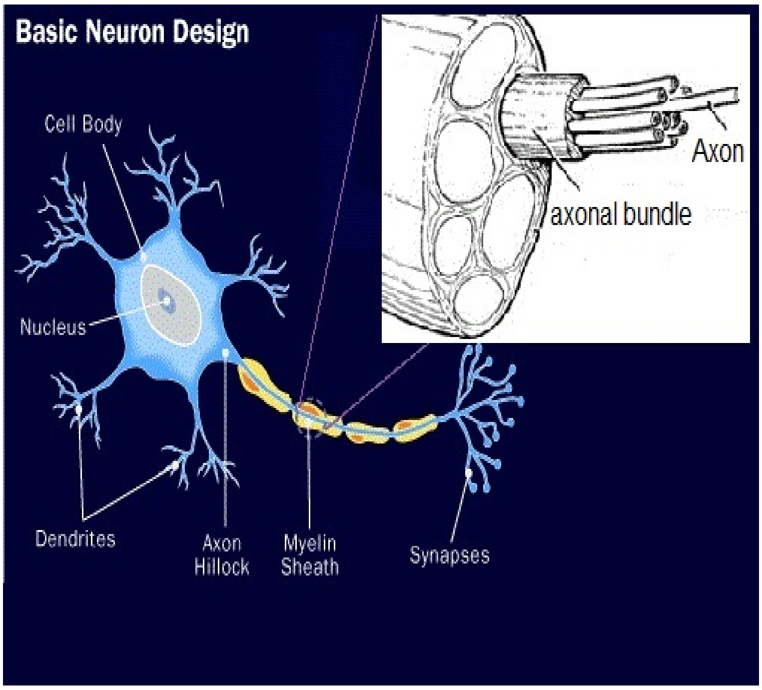

Figure 1.1: Structure of a typical neuron (Craig and Robynne, 2001)

The most commonly used diffusion MRI technique is diffusion weighted imaging (DWI) (Taylor and Bushell, 1985; Le Bihan and Breton, 1985). DWI is a non-invasive technique which may useful for detecting and characterizing the pathological and non-pathological features of living tissue. It is also very sensitive to water movements (molecular Brownian motion) (Yan, 2015). DWI is able to determine areas affected and healthy areas, but it can not provide details about the fibers directions in the MRI diffusion (Gass et al., 2004).

Diffusion Tensor Imaging (DTI) is the answer to the limitations of DWI through using tensors, which are mathematical tools capable of describing diffusion in different space directions, because diffusion is in most of the cases anisotropic [1] (Basser et al., 1994). DTI is a powerful technique to evaluate the major white matter fibre bundles. It also has a positive impact on disease prognosis, neurosurgical resection, and the preservation of brain function (Romano et al., 2009). Nevertheless, some challenges negatively affect the accuracy and validity of results of this technique.

Therefore, High Angular Resolution Diffusion Imaging (HARDI) was introduced by Tuch et al. (1999) to overcome the limitations of the DTI. HARDI requires a very large number of DWI. So, it provides more diffusion information (Alaya et al., 2017). Examples of the HARDI, Diffusion Spectrum Imaging (DSI) is developed to image complex distributions of intravoxel fibre orientation that is capable of mapping fibre architectures by imaging the 3D spectra of water molecules' displacement (Wedeen et al., 2000). Therefore, DSI is considered a model-free method (i.e., It does not assume a particular diffusion model, such as tensor model and multiple-tensor model) (Zucchelli et al., 2014; Sperl et al., 2017). However, the number of collected points from the q-space (q-space based techniques such as diffusion spectrum imaging, q ball imaging, and their variations have been used extensively in research for their desired capability to delineate complex neuronal architectures such as multiple fiber crossings in each of the image voxels) of DSI is more than ten times greater than DTI, this leads to long acquisition times and difficult to implement in a clinical application (Bilgic et al., 2012; Young et al., 2017). Thus, Q-Ball Imaging (QBI) was introduced by Tuch (2004a) to overcome the drawbacks of the DTI in the intravoxel heterogeneities of fibre orientation and the DSI problem

[1]Anisotropic is highly structured and typically have different diffusion coefficients along different directions (Tariq et al., 2016).

in the acquisition time. QBI computes the Orientation Density Function (ODF) which is the radial projection of the Probability Density Function (PDF) modeled as a spherical function able to represent crossing fibres (Pontabry et al., 2013; Fan et al., 2016).

Basically, the ODF is a criterion to determine the fibres' directions within a certain voxel. The fibre's path can be extracted in some directions corresponding to the highest orientation likelihood. In other words, an ODF may be considered as a deformed sphere whose radius in a given direction is proportional to the sum of values of the diffusion PDF in that direction (Hagmann et al., 2006). To further ease visualization, the surface of the ODF is colour coded according to a diffusion direction, as shown in Figure 1.2. Where x, y, and z coordinates refer to red, green, and blue, respectively (Topgaard, 2017).

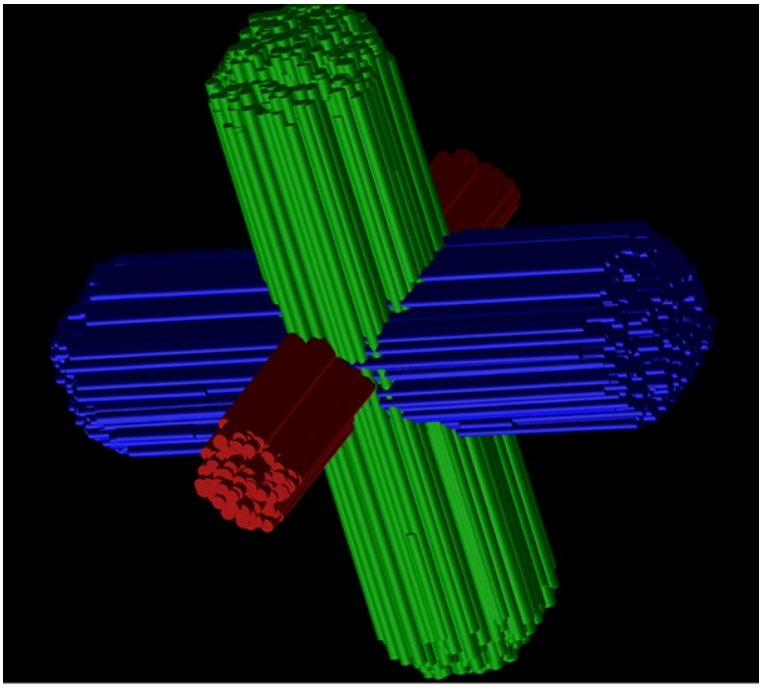

Figure 1.2: Color-encoded of the ODF according to a diffusion direction (Vos et al., 2013)

There are different ways can deal with ODF to improve the fiber directions such as deterministic methods, probabilistic methods, and optimization algorithms. This research is focused on the optimization algorithms to deal with the ODF for many reasons. For example, optimization algorithms seeking to find the best effective cost or achieving the highest possible level of interest (maximizing or minimizing) by systematically choosing the values of decision variables from a feasible set while satisfying a given set of constraints (Rao and Patel, 2013). Optimization algorithms proved its worth by achieving best results in different problems. For example, large tourism companies use optimization models to schedule routes and places to visit to achieve the maximum profit (Qiu et al., 2002). Shipping companies use optimization models to determine the best ship speed to reach its destination with the lowest fuel cost (Mansouri et al., 2015). Routers use optimization models to select the best path to forward data packets (Khedr et al., 2015).

1.1.2 Cuckoo Search Algorithm

The Cuckoo Search Algorithm (CSA) introduced by Yang and Deb (2009), it is inspired by the behavior of cuckoo breeding. CSA is based on the obligate brood parasitic behavior found in several cuckoo species combined with the *Lévy* flight behavior discovered in some birds and fruit flies. This algorithm has attracted attention since 2009 (Sheikholeslami et al., 2015).

Yang and Deb used a specific and simple representation for implementing CSA with each egg representing a solution. As each cuckoo lays only one egg, it also represents one solution. This representation aims to increase the diversity of new and probably good cuckoos (solutions) and to replace the unfit solutions. CSA can be complexed (i.e., representation) by using multiple eggs in each nest to represent a set of solutions.

The breeding behavior of a cuckoo is aggressive in nature, which inspires the optimization algorithms. Brood parasitism is a primary mechanism of a cuckoo, this bird lays eggs in the host's nest and carefully matches its eggs through mimicking the pattern and color (Rajabioun, 2011). In the case the host recognizes the cuckoo egg in its own nest, the host will either throw the egg out or simply leave its nest and build a new one. Therefore, a cuckoo must be accurate in its mimicry of the host eggs. By contrast, the host tries to improve its skills of determining the parasitic egg, which is called the struggle for survival.

The CSA provides solutions in a reasonable computational time and cost (Feng et al., 2014; Yang, 2014). This algorithm is more easily implemented compared to other population meta-heuristic algorithms such as Harmony Search (HS) and Genetic Algorithm (GA) because it has two parameters the probability of being discovered by the host bird P_α and the population n host nests. Therefore, CSA is one of the simplest algorithms and considered an effective search approach for solving complex optimization problems (Shehab, Khader and Al-Betar, 2017) (Mehdinejad et al., 2017). CSA also has two main operations: a random search based on the probability of the host bird to detect alien eggs and direct search based on *Lévy* flights (Kamalakannan et al., 2014). In other words, CSA balances between the global exploration and the deep exploitation in the search space. As such, CSA has been successfully applied to solve a broad range of real-world optimization problems (Li and Yin, 2016).

1.1.3 Why CSA has been chosen to solve the ODF

Swarm-based algorithms are optimization algorithms containing some algorithms inspired by nature such as artificial bee colony (ABC) (Karaboga, 2005), particle swarm optimization (PSO) (James and Russell, 1995), firefly algorithm (FA) (Yang and Algorithms, 2008), and CSA. These algorithms have many advantages over conventional algorithms. They combine rules and randomness to imitate some natural phenomena (Siddique and Adeli, 2015). In addition, they are efficient, highly adaptable, and tend to be flexible to implement. In other words, the features of these algorithms make it possible to use them in a wide range of problems in varied applications (Yang, 2015).

Based on the above, can be used any swarm-based algorithm to solve the ODF problem. However, during our research, we found that the CSA is the best choice to solve the ODF problem. For instance, no derivation information is required in the initial search, the number of parameters needed to be configured in the initial search is very little, and the inexperienced user can easily interact with it. CSA has a common specification with local search algorithms in exploitation through random walk and with evolutionary algorithms in exploration through *Lévy* flights. It is an efficient metaheuristic algorithm that balances between the local search strategy (exploitation) and the whole space (exploration) (Roy and Chaudhuri, 2013), deals with multi-criteria optimization problem, and aims for convergence speed and easy implementation. Furthermore, Precision in the mechanism of selection the solutions in the CSA is suitable for mechanism of the ODF to select the optimal point. In the CSA, the search is based on the *Lévy* flights, which moves between the solutions to determine a new solution and compares it with the random solution. It also uses the abandon of the worst solution (i.e., probability Pα) (i.e., there are two stages of each solution should pass through them). Therefore, the chosen solution should have a high fitness value to exceed these conditions. On the other hand, the ODF is obtained from diffusion weighted signals measured using the QBI. The spherical harmonics have been used to represent the ODF where each point in the sphere is represented through angle (θ, ϕ). Detecting the maxima of the ODF requires navigating between these points and extracting the maxima carefully. This process is available in the CSA in the selection solution. Due to these reasons, the CSA was selected to detect the ODF maxima. Nevertheless, There is no perfect algorithm 100 %. So, it's necessary to add some enhancements to ensure not to fall into the troubles. Such as low convergence, local traps, achieving weak results, etc.

1.2 Motivation and Problem Statement

The human brain is considered the center for neurons. As mentioned previously, this organ is responsible for sensorimotor and cognitive functions which is behind all aspects of human life. Brain pathologies or trauma lead most of the time to permanent disability and life quality deterioration, which require taking all kind of precautions when intervening on this organ.

Fibre tracking is a non-invasive tool (Dyrby et al., 2007) that is used to visualize and measure the pathways of white matter in the human brain initiated using the DTI (Wedeen et al., 1995; Weiss et al., 2015). Nevertheless, some challenges negatively affect the accuracy and validity of the results of this technique. For example, in the areas of complex intravoxel, the DTI technique fails to characterize the multiple fibre directions accurately in reconstructing crossing or kissing fibres (Wedeen et al., 2008; Kuhnt et al., 2013; Descoteaux and Deriche, 2015). Consequently, DTI fails to describe the diffusion process accurately, leads to influencing the efficiency of the fiber tracking algorithms.

The limitations of DTI have been overcome by introducing the QBI technique, which it is a variant of DWI that is sensitive to intravoxel heterogeneities in diffusion directions caused by crossing fibre tracts. QBI is a HARDI technique which has been proven very successful in resolving multiple fibre crossings and branchings in multiple intravoxel fibres using standard computation of ODF by directly sampling the diffusion signal on a spherical shell in diffusion space (Tomána et al., 2007). However, ODF still has a limitation in determining fiber directions which may be corrupted by neighbor directions (Assemlal et al., 2009).

In other words, in each voxel, the ODF is estimated independently of the information provided in the spatial neighborhood (Goh et al., 2009). Deterministic methods have been used by Thomas et al. (2014) to deal with such limitations. However, these methods suffer from local noise-induced disturbances which are additively accumulated along the track propagation, and lack of connectivity information between regions of the brain (Jones and Pierpaoli, 2005). Therefore, probabilistic methods have been employed by Vorburger (2012) to increase the accuracy of the local estimation along the path, but it also suffers from very long processing times, preventing their use in the clinical field (Parker, 2014). So, it is necessary to find alternative ways to address these limitations.

The optimization algorithm is a procedure which is executed iteratively by comparing different solutions till a satisfactory or an optimum solution is found (Deb, 2012). Wherefore, optimization will be conducted by employing the basic CSA (BCSA), which is considered a novel population-based stochastic global search metaheuristic algorithm (Zhao et al., 2012). According to the best knowledge available, BCSA efficiently handles the exploitation and exploration (Cuevas and Reyna-Orta, 2014). However, existing works have not investigated the BCSA in the context of the ODF in general. The focus of this dissertation is to adapt BCSA for ODF to extract all the fibres directions, then determine the maxima as a subset of the stationary points of the ODF with the possibility of controlling the convergence (balancing between slow and premature convergence) with increasing the quality and the efficiency of fiber direction. After that, enhancing its efficiency by combining components from metaheuristics.

1.3 Research Objectives

The main objectives of the research presented in this dissertation are as follows:

1. To propose a new method to extract the maxima of the orientation distribution function.
2. To enhance the proposed method by injecting heuristic-based techniques to improve the quality of the solution.

1.4 Research Contributions

The key contributions of this dissertation to the literature are:

1. Adapting the BCSA for ODF and extracting the ODF maximum, henceforth called Cuckoo Search Algorithm for Orientation Distribution Function (ACSA-ODF).

2. Introducing three versions of the BCSA with other metaheuristic components. These new versions can be described as follows:

   (a) **Modified Cuckoo Search Algorithm:**

   The Modified Cuckoo Search Algorithm (MCSA) is based on swapping the random selection (original) with tournament selection (proposed). Thus, the probability of better results is increased, through giving the solution that has the high fitness value a chance to be selected. That leads to increasing the quality of the solutions, increasing the diversity, and enhancing the convergence. MCSA is used to solve the ODF problem, namely, MCSA-ODF.

   (b) **Hybridization of modified cuckoo search algorithm with parts of the bat algorithm components**

   Hybridization of MCSA and some components of BA, namely, CSBA. This version starts with the MCSA to set up the population of host nests then looking for a new solution through the components of the BA. In such a way, CSBA focuses on the exploitation which leads to improving the convergence of the MCSA. The proposed version is used to solve the ODF problem, namely, CSBA-ODF.

   (c) **Hybridization of cuckoo search algorithm with Hill Climbing:**

   Hybridizing CSBA with local search -based algorithm (i.e., hill climbing (HC)), namely, CSAHC. This version proposed to overcome the drawbacks of the CSBA. In other words, the CSBA becomes more exploitative very fast and may stack at a local optimum. Thus, CSAHC used the mechanism of the HC as a new operator to increase its ability to find the local optimal solution in the search space. This version is used for solving the ODF problem which called CSAHC-ODF.

1.5 Scope of the Research

This research focuses on enhancing the performance of the BCSA to extract the ODF maxima, namely, ACSA-ODF. Three versions of the ACSA-ODF are introduced to improve the solutions and avoid the weaknesses: (i) MCSA-ODF, that replacing the current selection (i.e., random) with another selection scheme (i.e., tournament). MCSA-ODF is used to improve the fineness of the solutions by taking advantage of the features tournament selection scheme. (ii) CSBA-ODF, that hybridized the MCSA-ODF with components of the BA. CSBA-ODF is used to enhance the local search process (i.e, exploitation) that leads to avoiding the slow convergence. (iii) CSAHC-ODF, that hybridized CSBA-ODF with HC. CSAHC-ODF is used to improve the performance of CSBA-ODF through finding the local optimal solution with avoiding fall in the local traps.

1.6 Overview of Methodology

This section provides a brief discussion on the methodology, described fully in Chapter 4, to achieve the research objectives.

In Figure 1.3, stage 1 shows that after preparing the data, a new ODF maxima search approach using the BCSA has been proposed to extract all the ODF maxima (i.e., ACSA-ODF) which achieve the first objective, the synthetic data is used to evaluate the ACSA-ODF. To improve the performance of the ACSA-ODF, the approach is worthy of further research in order to achieve the second objective.

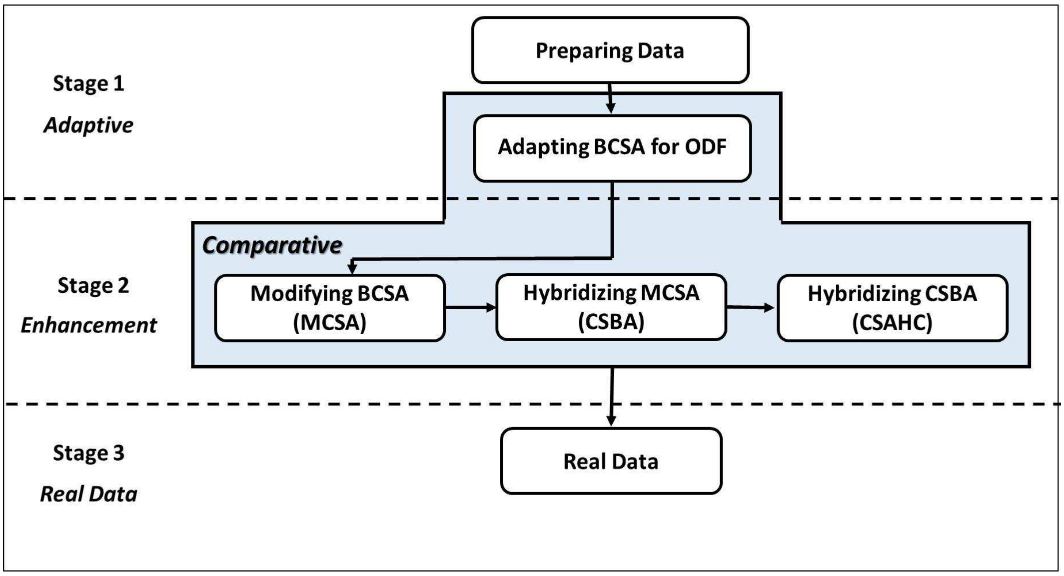

Figure 1.3: Research Methodology

Stage 2 shows the second objective which contains three techniques of effective components from metaheuristics were incorporated into BCSA. The first enhancement is the selection schemes concept from the tournament selection scheme used to enhance BCSA results by giving the opportunity for the best solution to be chosen (i.e., MCSA). The second enhancement is the hybridization which combines MCSA and a part from the BA (i.e., CSBA). This leads to focusing on the exploitation search which is characterized by BA thereby overcoming the slow convergence suffered by the MCSA. The third enhancement is the local search-based algorithm hybridization that combines CSBA and HC operator (i.e., CSAHC) to improve the local exploitation of the CSBA. For evaluation each version of BCSA (without ODF; MCSA, CSBA, and CSAHC) a set of benchmark functions are used, while the synthetic data is used to evaluate the performance of each version of the ACSA-ODF (with ODF; MCSA-ODF, CSBA-ODF, and CSAHC-ODF).

1.7 Overview of the Dissertation

This dissertation includes nine chapters organized as follows: Chapter 2 discusses the cuckoo search algorithm in details; procedure, growth, and variants of CSA.

Chapter 3 provides an overview of the diffusion MRI. It also surveys some previous methods that tackled the ODF problems. The methodology is proposed and described in details in Chapter 4.

Chapter 5 is divided into two main parts. The first part, introduces the steps of preprocessing such as generate the synthetic data. The second part, describes the adaptive BCSA to solve ODF (ACSA-ODF), then evaluate fiber detection success through using the synthetic data.

Chapters 6 and 7 illustrate the Modification (MCSA-ODF) and two types of hybridization (CSBA-ODF, CSAHC-ODF), consecutively. The experiments and results with detailed analysis of studying are presented at each chapter. It should be noted that the experiments were done through two stages of evaluation. 1) Applied set of benchmark functions optimization, followed by 2) Applied synthetic data.

Finally, in Chapter 8 a summary of claimed results and future possibilities are provided. It is hoped that the reader will be challenged to prove or disprove the claims made throughout this dissertation, and extend the research in new directions.

CHAPTER 2

CUCKOO SEARCH ALGORITHM

2.1 Introduction

Optimization problem exists in many domains, such as engineering, energy, economics, medical, and computer science. It is mainly concerned with finding the optimal values for several decision variables to form a solution to optimization problem. This solution is considered optimal when the decision maker is satisfied with it. An optimization problem is the minimization or maximization of a suitable decision-making algorithm normally adapted to the approximation methods. The principle of decision making entails choosing between several alternatives. The result of this choice is the selection of the best decision from all choices.

Optimization algorithms developed based on nature-inspired ideas deal with selecting the best alternative based on the given objective function. This chapter is limited to the metaheuristic algorithm which it is a general solver template. Where, it can be adapted for various kinds of optimization problems by properly tweaking its operators and configuring its parameters. To elaborate, each optimization algorithm can be categorized into three classes: evolutionary algorithms (EAs), swarm-based algorithms, and trajectory-based algorithms (Shehab, Khader and Al-Betar, 2017). EAs mimic the evolutionary principle of survival of the fittest. It normally begins with a set of individuals (i.e., a group of solutions) called population. At each generation, the EA algorithms recombine the preferable characteristics of the current population to come up with a new population that will be selected based on the natural selection principle. Examples of EAs include genetic algorithms (GAs) (Holland, 1975), genetic programming

(GP) (Koza, 1994), differential evolution (DE) (Storn and Price, 1996), and harmony search algorithm (HSA) (Geem et al., 2001). On the other hand, swarm-based algorithms mimic the behavior of a group of animals when searching for survival. At each iteration, the solutions are normally constructed based on historical information gained by previous generations (Bolaji et al., 2016). Examples of swarm-based algorithms include artificial bee colony (ABC) (Karaboga, 2005), particle swarm optimization (PSO) (James and Russell, 1995), firefly algorithm (FA) (Yang and Algorithms, 2008), and cuckoo search algorithm (CSA) (Yang and Deb, 2009). Trajectory-based algorithms start with a single provisional solution. At each iteration, that solution will be moved to its neighboring solution, which resides in the same search space region, using a specific neighborhood structure. Examples of trajectory-based algorithms includes tabu search (TS) (Glover, 1977), simulated annealing (SA) (Kirkpatrick et al., 1983), hill climbing (Koziel and Yang, 2011), and β-hill climbing (Al-Betar, 2016).

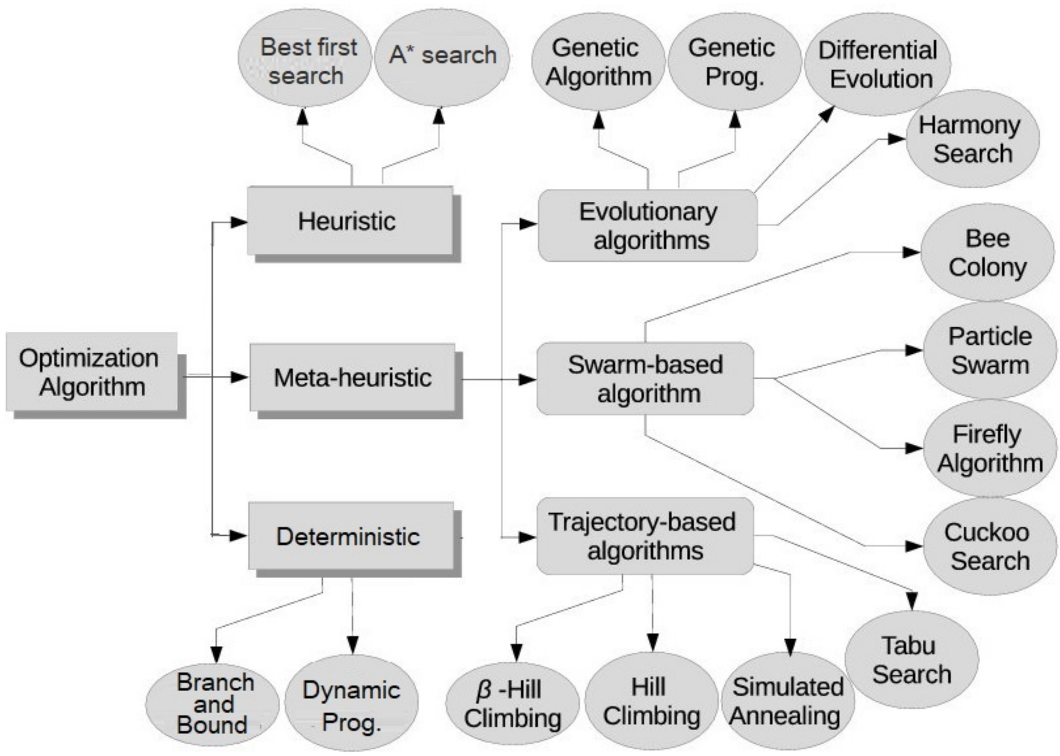

Figure 2.1: Optimization Algorithms

The main merits of the CSA over other optimization algorithms are as follows: it has fewer parameters, and one of the most powerful features of CSA is the use of *Lévy* flights to generate new candidate solutions (Karthik et al., 2017) (Esapour et al., 2015). Owing to these merits, the CSA has been successfully tailored to a wide variety of optimization problems, such as constrained optimization (Ong and Kohshelan, 2016), in medical field (Giveki et al., 2012; Liu and Fu, 2014; Stewart et al., 2016), clustering and data mining (Goel et al., 2011; Amsaleka and Latha, 2014; Cobos et al., 2014), image processing (Pare et al., 2016; Tiwari, 2012; Bhandari, Singh, Kumar and Singh, 2014; Bhandari, Soni, Kumar and Singh, 2014; Agrawal et al., 2013; Raja and Vishnupriya, 2016), economic dispatch problems (Tran et al., 2015; Basu and Chowdhury, 2013; Vo et al., 2013; Pham et al., 2016; Sekhar and Mohanty, 2016), engineering design (Gandomi, Talatahari, Yang and Deb, 2013; Ahmed and Salam, 2014; Bhargava et al., 2013; Esfandiari, 2014; Gandomi, Yang and Alavi, 2013; Kaveh and Bakhshpoori, 2013, 2016), and power and energy (Ahmed and Salam, 2013; Buaklee and Hongesombut, 2013; Devabalaji et al., 2016; Elazim and Ali, 2016; Femia et al., 2005; Ma et al., 2013; Machowski et al., 2011).

The CSA is also modified and hybridized for the convenience of some combinatorial optimization problems because of the complex nature of some optimization problems (Walton, Hassan, Morgan and Brown, 2011; Giridhar et al., 2016; Babukartik and Dhavachelvan, 2012; Wang, Gandomi, Zhao and Chu, 2016; Lim et al., 2016; Layeb and Boussalia, 2012; Shatnawi and Nasrudin, 2011; Noghrehabadi et al., 2011). The parameter setting of the CSA is also addressed by several researchers Tuba et al. (2011); Abdul Rani et al. (2012); Tawfik et al. (2013); Li and Yin (2016).

This chapter provides a comprehensive and exhaustive overview of the theoretical aspects of CSA and presents the readers with sufficient materials for the previous adaptation, modification, and hybridization of the CSA. It also focuses on the principles of CSA, its developments and variants to the original CSA, and a detailed report of recent applications and associated developments attained during the last few years.

This chapter is organized as follows. Section 2.2 introduces the CSA by highlighting its framework. Section 2.3 discusses the procedure of the basic CSA, then the variants of CSA are shown in details in Section 2.4, followed by related works of hybridization BCSA in Section 2.6. Finally,The conclusion is presented in Section 2.6.

2.2 Cuckoo Search Algorithm Inspired from Nature

There are more than 1,000 species of birds in nature, and these birds share some approaches with one another (Rajabioun, 2011). For example, all mother birds lay eggs that have different shapes of eggs from one another. Moreover, different nests are built by many birds in isolated places to increase safety from predators (Davies, 1970).

Birds that resort to cunning approaches for reproduction, specifically in building nests, are called "brood parasites". These kinds of birds do not build their own nests but rather lay their eggs in the nest of another species, leaving the host to care for its young. The most famous of the brood parasites is the cuckoo. It has a fantastic way in the art of deception. Its strategy involves permeation by removing one egg laid by the host and laying her own. It then carefully matches its egg through mimicking the pattern and color of the host's eggs, a skill that requires high accuracy to ensure its success. The timing of egg-laying is also an amazing way of selecting the nest where the host bird just laid its own eggs (Khan and Sahai, 2013). This process will reap benefits after a while; the cuckoo egg will hatch before the host eggs, and the first instinctive action of the host will be to evict its own eggs out of the nest by blind propelling, thus increasing the care and food provided for the cuckoo's chicks. Cunningness is inherited by the chicks; this trait is shown when the chicks mimic the call of host chicks to gain access to more feeding opportunity (Yang and Press, 2010).

On the other hand, in case the host recognizes the cuckoo's egg in its nest, they either throw out the strange egg or simply leave their own nest and build a new one. The cuckoo must therefore be more accurate in mimicking the host eggs, whereas the host must improve its skills in determining the parasitic egg. Therein lies the so-called struggle for survival.

The use of CSA in the optimization context was proposed by Yang and Deb in 2009. To date, work on this algorithm has significantly increased, and the CSA has succeeded in having its rightful place among other optimization methodologies (Fister Jr et al., 2014; Yang and Deb, 2009). This algorithm is based on the obligate brood parasitic behavior found in some cuckoo species, in combination with the *Lévy* flight , which it is a type of random walk which has a power law step length distribution with a heavy tail. It is inspired from behavior discovered of some birds and fruit flies. Also, it has been found (Brown et al., 2007; Pavlyukevich, 2007) that *Lévy* flights is an oft-observed random walk in real life (Viswanathan et al., 1999, 2002). The CSA is an efficient metaheuristic swarm-based algorithm that efficiently strikes a balance between local nearby exploitation and global-wide exploration in the search space problem (Roy and Chaudhuri, 2013).

The cuckoo has a specific way of laying its eggs to distinguish it from the rest of the birds (Yang and Deb, 2014). The following three idealized rules clarify and describe the standard cuckoo search:

- Each cuckoo lays one egg at a time and dumps it in a randomly chosen nest.
- The best nests with high-quality eggs will be carried over to the next generations.
- The number of available host nests is fixed, and the egg laid by a cuckoo is discovered by the host bird with a probability $P\alpha \in (0,1)$. In this case, the host bird can either get rid of the egg or simply abandon the nest and build a completely new nest. In addition,

probability $P\alpha$ can be used by the n host nest to replace the new nests.

2.3 The procedure of basic cuckoo search algorithm

The basic CSA procedure is established by Yang and Deb (2009), the founders of CSA. Figure 2.2 shows a flowchart of the CSA. Similar to other swarm-based algorithms, the CSA starts with an initial population of n host nests. These initial host nests will be randomly attracted by the cuckoos with eggs and also by random *Lévy* flights to lay the eggs. Thereafter, nest quality will be evaluated and compared with another random host nest. In case the host nest is better, it will replace the old host nests. This new solution has the egg laid by a cuckoo. If the host bird discovers the egg with a probability $P\alpha \in (0,1)$, the host either throws out the egg, or abandons it and builds a new nest. This step is done by replacing the abundant solutions with the new random solutions.

Yang and Deb used a certain and simple representation for the implementation, with each ***egg*** representing a solution. As the ***cuckoo*** lays only one egg, it also represents one solution. The purpose is to increase the diversity of new, and probably better, cuckoos (new solutions) and replace them instead with the worst solutions. By contrast, the CSA can be more complicated by using multiple eggs in each nest to represent a set of solutions.

The CSA, as a bat algorithm (Yang, 2010b) and an FA (Yang, 2010a), uses a balance between exploration and exploitation. The CSA is equiponderant to the integration of a *Lévy* flights. When generating new solutions x^{t+1} for, say, a cuckoo i,a *Lévy* flight is performed

$$x_i^{t+1} = x_i^t + \alpha \bigoplus Le'vy(\lambda) \tag{2.1}$$

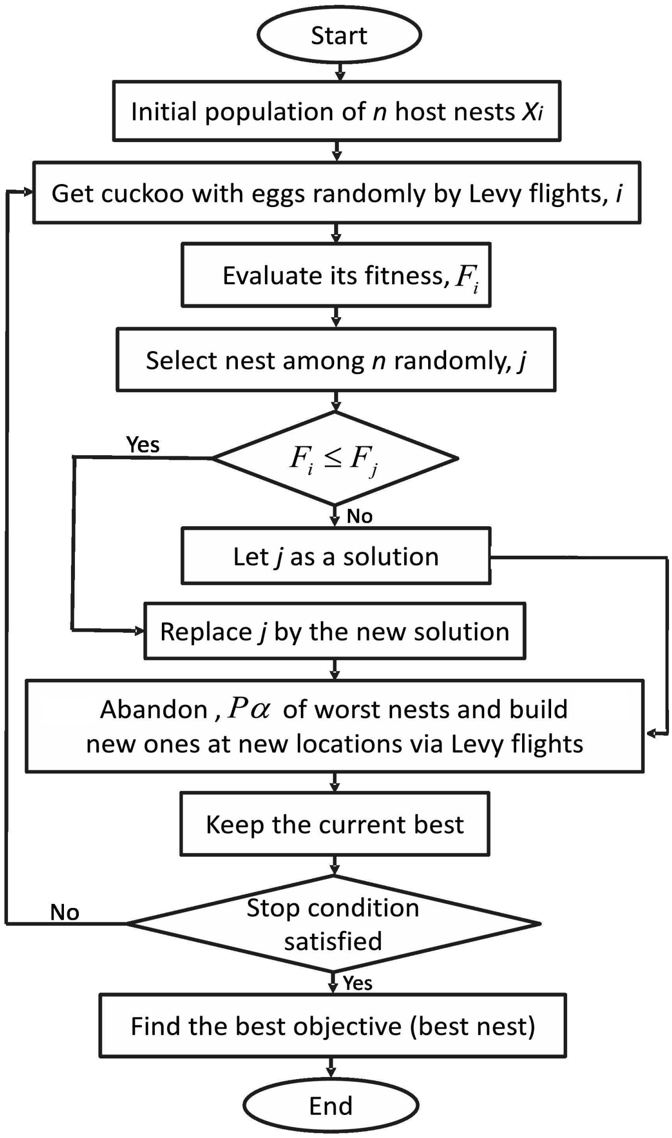

Figure 2.2: Flowchart of Cuckoo Search Algorithm (Abdul Rani et al., 2012)

where $\alpha > 0$ is the step size which should be related to the scales of the problem of interests. In most cases, we can use $\alpha = 1$. The x_i^t in the equation 2.1 represents the current location, which is the only way to determine the next location x_i^{t+1}. This is called the random walk and the Markov chain. The product $\bigoplus$ means entrywise multiplications. This entrywise product is similar to those used in PSO, but here the random walk via *Lévy* flight is more efficient in exploring the search space as its step length is much longer in the long run. A global explorative random walk by using *Lévy* flights can be expressed as follows:

$$Lèvy \sim u = t^{-\lambda}, \quad 1 < \lambda \leqslant 3 \tag{2.2}$$

where λ is a parameter which is the mean or expectation of the occurrence of the event during a unit interval. Here the steps essentially form a random walk process with a power law step-length distribution with a heavy tail. Some of the new solutions should be generated by *Lévy* walk around the best solution obtained so far, this will speed up the local search. However, a substantial fraction of the new solutions should be generated by far field randomization and whose locations should be far enough from the current best solution, this will make sure the system will not be trapped in a local optimum. Algorithm 1 shows the representation of the CSA search process.

Algorithm 1 Basic Cuckoo Search algorithm

Objective function $f(X), X = (x_1, ...x_d)^T$
Generate initial population of n host nests $Xi(i = 1, 2, ..., n)$
while $t < Max\_iterations$ **do**
  $(t < MaxGeneration)$ or (stop criterion)
  Get a cuckoo randomly by Levy flights
  evaluate its quality $fitnessF_i$
  Choose α nest among n (say, j) randomly
  if $F_i > F_j$ **then**
    replace j by the new solution;
  end if
  A fraction $(P\alpha)$ of worse nests are abandoned and new ones are built;
  Keep the best solutions (or nests with quality solutions);
  Rank the solutions and find the current best
end while
Postprocess results and visualization

2.4 Cuckoo search algorithm variants

The CSA proposed in 2009 is a recent swarm-based algorithm in comparison with the firefly, bee colony, PSO, and ant colony algorithms proposed in 2008, 2005, 1995, and 1992, respectively. However, the CSA has been updated for several variants developed by researchers to cope with the nature of the search space of the optimization problem. Most of these variants will be extensively but not exhaustively described.

2.4.1 Binary Cuckoo Search Algorithm

Gherboudj et al. (2012) proposed a discrete binary cuckoo search (BCS) algorithm for binary optimization problems. The solutions are represented in the optimization problems either by a set of real numbers (called continuous optimization) or by a set of integer numbers (called discrete optimization). The discrete optimization problem class has some subclasses, such as discrete binary optimization problems, and its solutions are represented by a set of bits, including routing (Zhan and Zhang, 2009), job shop scheduling (Pongchairerks, 2009), and flowshop scheduling problems (Liao et al., 2007). This BCS variation uses a sigmoid function to create a bridge between the discrete/the continuous and the binary values.

As aforementioned, the CSA is based on *Lévy* flights. Therefore, the solutions present as a set of real numbers working in a continuous search space. The solutions must be converted to binary values to extend the CSA to discrete binary areas. The BCS is designed to contain two basic modules:

- Main binary cuckoo dynamics: this module includes two operations:
  - *Lévy* flights: it used to obtain a new cuckoo.
  - Binary solution representation (BSR) to compute the flipping chances for each cuckoo by using the sigmoid function. After that, the flipping chance of each cuckoo to calculate the binary value is used.
- Objective function and the selection operator: the selection operator principles presented here is the same as presented for genetic algorithms

To convert from the continuous area to the binary area, assume x_i is a solution of continuous nature in the interval [0, 1] and $x_i^{'}$ is a BSR, the sigmoid function will convert the values as follows:

$$S(x_i) = \frac{1}{1+e^{-x_i}} \tag{2.3}$$

where $S(x_i)$ is the flipping chance of bit $x_i^{'}$. To obtain the binary solution $x_i^{'}$, $S(x_i)$ is compared to the result of the generated random number from the [0, 1] interval for each dimension i of solution x as shown in following equation:

$$x_i^{'} = \leftarrow \begin{cases} 1 & \gamma < S(x_i) \\ 0 & otherwise \end{cases}$$

where γ is a random number between [0,1]. In case the flipping chance of bit $x_i^{'}$ is bigger than the random number then the value is 1, otherwise the value is 0.

2.4.2 Discrete Cuckoo Search Algorithm

The TSP is a classical optimization problem used to evaluate any new development. The TSP principle is that the salesman must visit each city once, starting and finishing from a certain one with a minimum total length of the trip. Ouaarab et al. (2014) introduced a DCSA for the TSP. The author improved and developed the CSA through rebuilding the population and proposing a new category of cuckoos. Thus, DCSA efficiency was increased with less iterations. The DSCA can also solve the continuous and combinatorial problems. It increases the protection of local optima in the case of TSP from stagnation. This supports the DCSA to have more control over the diversification and intensification with less parameters. The experimental analysis of the results showed that the performance of the proposed DCSA algorithm was highly effective compared with genetic simulated annealing ant colony system with particle swarm optimization techniques (GSA-ACS-PSOT) (Chen and Chien, 2011) and discrete PSO (Shi et al., 2007).

In another study, DCSA was proposed to solve TSP by Jati et al. (2012). The authors proposed two phases and called them schemes. The first scheme proposed, discrete step size, refers to the distance between the cuckoo and the best cuckoo in its generation. The second scheme is where the cuckoos were updated using a step size α and a random step length drawn from the *Lévy* distribution called *Lévy* flight. The results proved the performance of DCSA with simple TSP. However, it could not achieve the optimal solution for complex TSP. Gherboudj et al. (2012) proposed a discrete binary CSA (DBCSA) to solve 0-1 knapsack problems. The authors used a sigmoid function to obtain binary solutions, which are the same as those used in binary PSO. This work has two objectives. The first objective copes with the binary optimization problems, where the basic CSA solution consists of a set of real numbers. On the other hand, the DBCSA solution consists of a set of bits by using a sigmoid function and a probability model to generate binary values. The second objective proves the effectiveness of the basic CSA dealing with binary combinatorial optimization problems. The experimental results on both the multidimensional knapsack problem instances showed the effectiveness of the BDCSA and its ability to obtain good quality solutions compared with the quantum-inspired CSA (QICSA), HS, and binary PSO (Kennedy and Eberhart, 1997).

2.4.3 Modified cuckoo search algorithm

Tuba et al. (2011) proposed modified CSA (MCSA) for unconstrained optimization problems. The authors modified the basic CSA by determining the step size from the sorted rather than only the permuted fitness matrix. For example, if the similarity between the cuckoo's egg and the host's eggs was very high, the likelihood of discovery was reduced; therefore, fitness