Butterfly Mating Optimization for Dynamic Multimodal Search Space

A mini project report submitted in fulfilment of the requirements for the completion of MiniProject

by

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Certificate

It is certified that the work contained in this mini project entitled**'Butterfly Mating Optimization for Dynamic Multimodal Search Space'** by

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has been carried out under my supervision and that it has not been submitted elsewhere for a degree.

Project Guide

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Abstract

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Most of the real world problems today can be related to as Multimodal optimization problems and recently algorithms to find them have been widely studied. This project also develops a novel swarm intelligence algorithm named as Butterfly Mating Optimization (BMO) which is based on the mating phenomena occurring in butterflies.The agents in BMO are thought of as Butterflies (Bflies) reflecting and absorbing UV light and encoding function profile with their UV. A Bfly's choice of mate selection depends on the value of UV its absorbs meeting a certain criteria called as l-mate selection. This behaviour follows the natural behaviour of butterflies patrolling and perching in the open fields based on the traits like colour, size and UV reflections. We present this BMO algorithm with novel concept of dynamic local mate selection process which plays a major role in capturing multiple peaks for dynamically varying multimodal search spaces.a complete survey on Biological behaviour of Butterflies was done .

Acknowledgements

We extend our deepest gratitude to all those who have been a part of our mini project. Thank you very much for being there for us to put our ideas well above the level of simplicity.Nothing of this would have been possible without the blessings of our parents to whom we were indebted so much.We would also like to thank each and every person individually who helped us in accomplishing this project.

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Last but not the least, We take this opportunity to thank all the faculty and staff of ECE Department, who directly or indirectly helped us with their generous guidance and all the friends for being our continuous source of strength and motivation in all our efforts.

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Abbreviations

SI	**S**warm **I**ntelligence
PSO	**P**article **S**warm **O**ptimization
BMO	**B**utterfly **M**ating **O**ptimization
GSO	**G**lowworm **S**worm **O**ptimization

Symbols

f(t)	Fitness of the bfly
UV_i	UV of i^{th} bfly
$UV_{i \to j}$	UV absorbed by j^{th} bfly which reflected by i^{th} bfly
d_{ij}	Euclidean distance between i^{th} bfly and j^{th} bfly

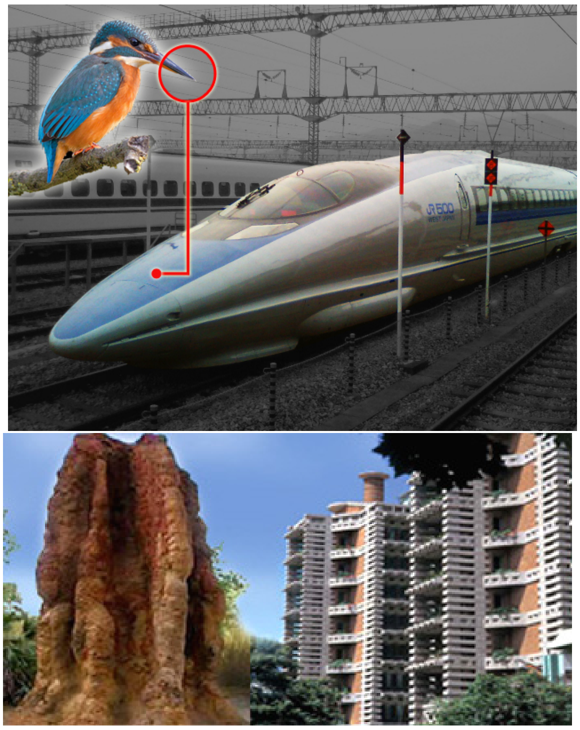
Chapter 1

Introduction

Nature is great and immense source of inspiration to the mankind in various aspects. Each species of nature has their own way of accomplishing the tasks in their daily routine. They developed a robust , dynamic, diverse system to survive in this nature undergoing some mechanisms through which it can feed, communicate, reproduce and defend itself. They use local natural resources which are continuously recycled, reused and renewed. This is what that attracted the human beings to mimic nature to solve the most of hard and complex problems of the today world.

1.1 Inspiration from Nature

Taking inspiration from the nature, man invented and built the powerful things which totally changed the today world. Shinkansen bullet train was constructed based on the kingfisher beak .It not only reduced the noise of the train but was also more aerodynamic using less power and enabling higher speeds.With their rotor like design ,maple seeds whirl in the air as they fall –the lift generated through the spinning allow them to travel much further from the tree.Lockheed martin adapted this design for single rotor drone called Samarai.Based on the honey bees living in bee hive ,Regen energy in the US found a way to improve the efficiency of energy grids.African termites have evolved some clever designs to keep their mounds at nearly constant temperature thought outside it may swing from 40C in the day to lessthan 2C at night. Using this phenomenon , Architect Mick Pearce designed a building named Eastgate building in Zimbabwe. The building stays cool without air conditioning and so uses only a tenth of energy of conventional building of the same size.



A single ant or bee is neither efficient nor intelligent. But when they formed into large groups they can achieve the task easily when compared with individuals performance. Ants form into colonies to find the food. They leave trail of pheromones when they leave nest.When an ant find the food it follows different pheromone trail to the nest.The remaining ants sense these pheromones through their receptors and finds the food by sensing all the pheromones along the path.

Flock of birds show great coordination when they are foraging or migrating. Every individual bird in the flock adjust its movement to coordinate with the neighbors. They don't take any orders from any member of flock as there is no lead bird.The flock aims to achieve the global objective through their non centralized behavior.

Fish evolved to swim in schools to protect themselves from the predators. Predators can easily attack a single fish but it is difficult when fish swim in schools. Because when predator is about to attack they escape by performing maneuvers. There is no centralized authority among the fish when they are in schools. Each fish move according to its neighbor fish so as to coordinate with the entire school.

All these ants, birds, fish , bees, bats etc., show some collective behavior when they are in groups.This collective behavior is called Swarm Intelligence. Using this swarm intelligence many natural systems have emerged into powerful tools which make their survival possible. Based on this swarm intelligence many algorithms took shape to solve the most complex problems and most of them are optimization algorithms.

1.2 Field Of Optimization

In engineering discipline, optimization means selection of best element from a set of available alternatives. Selection is based on definite criteria. Optimization is the most encountered problem in engineering and technology.It can be modelled as set of real numbers from which we have to select the best(either the maximum or minimum) value as our solution. Many real-world and theoretical problems may be modelled in this general framework. Major subfields of Optimization includes, linear programming, geometric programming, non linear programming, stochastic optimization, combinatorial optimization, heuristics and meta-heuristics etc. Optimization problems are often multi-modal; that is, they possess multiple good solutions. They could all be globally good (same cost function value) or there could be a mix of globally good and locally good solutions. Obtaining all (or at least some of) the multiple solutions is the goal of a multi-modal optimizer. Multimodal function optimization generally focuses on algorithms to find either a local optimum or the global optimum.

The knowledge of multiple local and global optima has several advantages such as obtaining an insight into the function landscape and selecting an alternative solution when dynamic nature of constraints in the search space makes a previous optimum solution infeasible to implement[3]. Knowledge of multiple solutions to an optimization task is especially helpful in engineering, when due to physical (and/or cost) constraints, the best results may not always be realizable. In such a scenario, if multiple solutions (local and

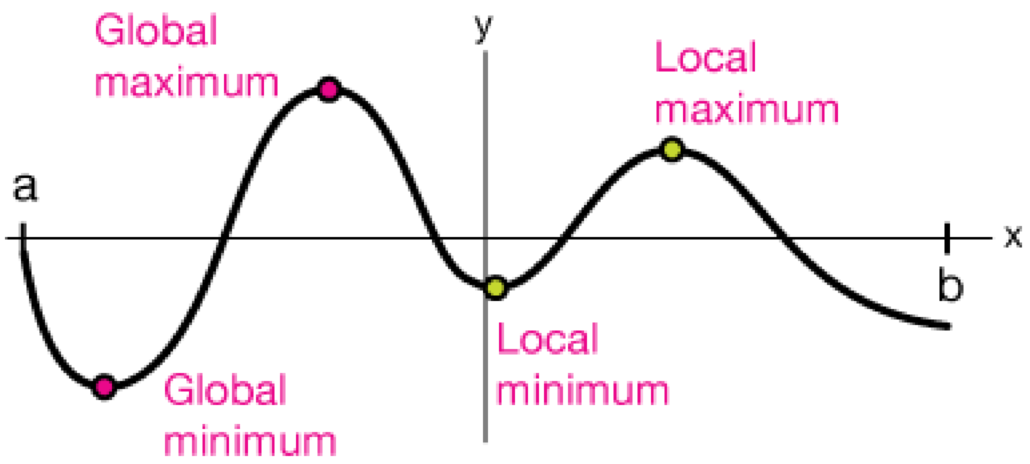


FIGURE 1.1: A function with global and local maxima and minima.

global) are known, the implementation can be quickly switched to another solution and still obtain an optimal system performance. Multiple solutions could also be analyzed to discover hidden properties (or relationships), which makes them high-performing. In addition, the algorithms for multimodal optimization usually not only locate multiple optima in a single run, but also preserve their population diversity, resulting in their global optimization ability on multimodal functions. Moreover, the techniques for multimodal optimization are usually borrowed as diversity maintenance techniques to other problems [4]. These problems find applications in swarm intelligence for self assembly, image classification, data mining, signal source localization, collective robots, uncertainty estimation etc.

In the next chapter, description of experiments conducted based on natural behavior of organisms is given in brief before the detailed explanation of the already existing algorithms for Multimodal Optimization problems.

Chapter 2

Literature Survey

2.1 Biologically Inspired Experiments

Many experiments were done to deeply study the natural behaviour of bio-organisms and two experiments based on the behaviour of ant colonies and flock of birds that have inspired the proposal of two of the best algorithms in the field of optimization are given below.

2.1.1 Double Bridge Experiment

Ant colonies are distributed systems that present a highly structured social organization through which they can accomplish complex tasks that in some cases far exceed the individual capabilities of a single ant. The field of "ant algorithms" studies models derived from the observation of real ants' behavior, and uses them as a source of inspiration for the design of novel algorithms for the solution of optimization and distributed control problems. Several different aspects of the behavior of ant colonies have inspired different kinds of ant algorithms. Examples are foraging, division of labor, brood sorting, and cooperative transport. In all these examples, ants coordinate their activities via stigmergy, a form of indirect communication mediated by modifications of the environment. Stigmergy is an indirect, non-symbolic form of communication mediated by the environment and its information is local. This is also observed in colonies of ants [5].

Deneubourg et al. [6] thoroughly investigated the pheromone laying and following behavior of ants. In an experiment known as Double Bridge Experiment, the nest of colony of Argentine ants was connected to food source by bridges of equal length. In such a setting, ants start to explore the surroundings of the nest and eventually reach the food source by depositing pheromone along the path. Initially, each ant randomly chooses one of the two bridges. However, due to randomness, after some time one of the two bridges presents a higher concentration of pheromone than the other and, therefore, attracts more ants. This brings a further amount of pheromone on that bridge making it more attractive and after some time the whole colony converges toward the use of the same bridge. This colony-level behavior, based on the exploitation of positive feedback, can be used by ants to find the shortest path between a food source and their nest.

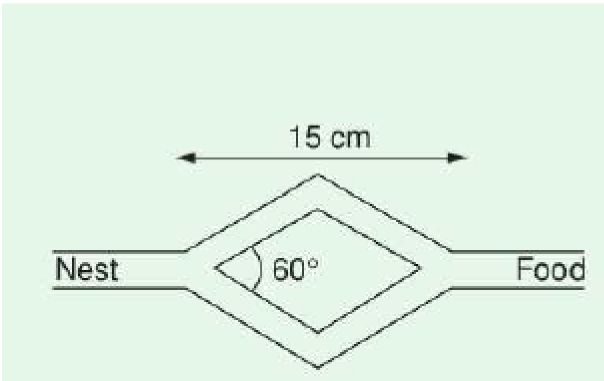


Figure 2.1: Double Bridge Experiment: Bridges of equal lengths.

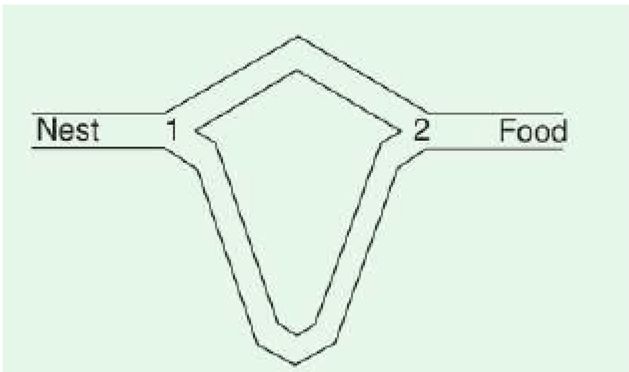


Figure 2.2: Double Bridge Experiment: Bridges of unequal lengths.

Goss et al. [7] considered a variant of this experiment in which one bridge is significantly longer than the other. The short bridge receives, therefore, pheromone earlier than the long one and this fact increases the probability that further ants select it rather than the long one. The model proposed by Deneubourg and co-workers for explaining the foraging behavior of ants was the main source of inspiration for the development of ant colony optimization.

2.1.2 Flocks, Herds, and Schools: A Distributed Behavioural Model

The motion of a flock of birds is one of nature's delights. Flocks and related synchronized group behaviours such as schools of fish or herds of land animals are both beautiful to watch and fascinating to contemplate. A flock exhibits many contrasts. It is made up of discrete birds yet overall motion seems fluid; it is simple in concept yet is so visually complex, it seems randomly arrayed and yet is magnificently synchronized. Perhaps most puzzling is the strong impression of intentional, centralized control. Yet all evidence indicates that flock motion must be merely the aggregate result of the actions of individual animals, each acting solely on the basis of its own local perception of the world.

Craig W. Reynolds [8] explored an approach based on simulation as an alternative to scripting the paths of each bird individually. This approach assumes a flock is simply the result of the interaction between the behaviours of individual birds. To simulate a flock he simulated the behavior of an individual bird (or at least that portion of the bird's behavior that allows it to participate in a flock). He started with a boid model that supports geometric flight and added behaviours that correspond to the opposing forces of collision avoidance and the urge to join the flock. Stated briefly as rules, and in order of decreasing precedence, the behaviours that lead to simulated flocking are:

1. Collision Avoidance: avoid collisions with nearby flockmates
2. Velocity Matching: attempt to match velocity with nearby flockmates
3. Flock Centering: attempt to stay close to nearby flockmates

The model of polarized non colliding aggregate motion has many applications, visual simulation of bird flocks in computer animation being one. Other applications are less obvious. Traffic patterns, such as the flow of cars on a freeway, is a flock-like motion. We could imagine creating crowds of "extras" (human or otherwise) for feature films. One

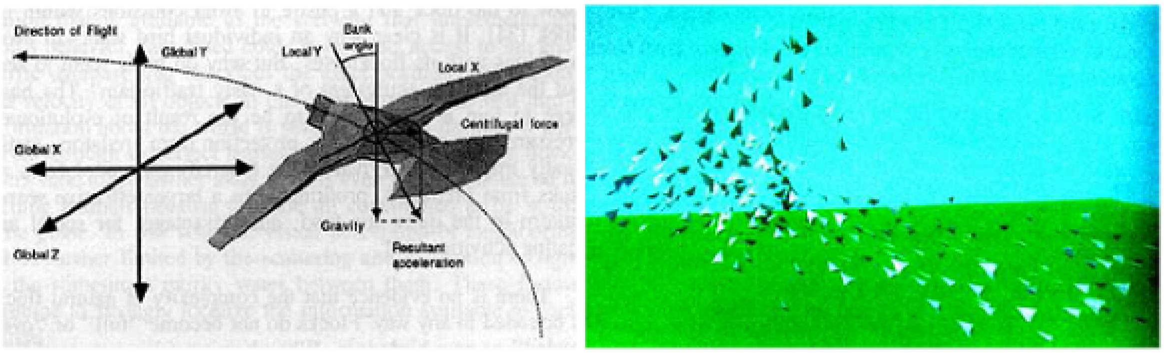


FIGURE 2.3: Forces acting on each bird and the animation simulated.

serious application would be to aid in the scientific investigation of flocks, herds, and schools. A theory of flock organization can be unambiguously tested by implementing a distributed behavioural model and simply comparing the aggregate motion of the simulated flock with the natural one. This work of Reynolds was hence able to inspire Kennedy et. all [9] to propose Particle Swarm Optimization (PSO), a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality.

2.2 Algorithms proposed for solving Multimodal Optimization problems

Population-based approaches are particularly suited to solving multimodal function optimization problems and could be broadly divided into two categories: evolutionary computation (EC) techniques that are based on evolutionary mechanisms encountered in natural selection and swarm intelligence (SI) methods.Seeking multiple optima by maintaining population diversity has received some attention in the domain of genetic algorithms and particle swarm optimization algorithms.Traditional genetic algorithms (GAs) [10] can successfully identify the best rule (optimum) in the domain, but are incapable of maintaining rules of secondary importance.

Parsopoulos et. al [11] studied altering the fitness value via fitness function stretching to adapt PSO to sequentially find peaks in a multimodal environment. In particular, a potentially good solution is isolated once it is found (if its fitness is below a threshold value) and then the fitness landscape is stretched to keep other particles away from this area of the search space. The isolated particle is checked to see if it is a global optimum, and if it is below the desired accuracy, a small population is generated around this particle to allow a finer search in this area. The main swarm continues its search for the rest of the search space for other potential global optima.

Brits et al. [12] proposed a niching particle swarm optimization (NichePSO) algorithm, which has some improvements to the Parsopoulos and Vrahitiss model. The NichePSO is a parallel niching algorithm that locates and tracks multiple solutions simultaneously.Kennedy investigated modifying the PSO algorithm with stereotyping where clustering based on particles previous position, with cluster centers substituted for individuals or neighbors previous bests, forces the clusters to focus on local regions.

K.N. Krishnanand and D. Ghose [13] developed a novel Glowworm Swarm Optimization for simultaneously capturing the multiple optima of multimodal functions. The algorithm shares some features with the ant-colony optimization (ACO) and particle swarm optimization (PSO) algorithms, but with several significant differences. The agents in the GSO algorithm are thought of as glowworms that carry a luminescence quantity called luciferin along with them. The glowworms encode the function-profile values at their current locations into a luciferin value and broadcast the same to other agents in their neighbourhood. The glowworm depends on a variable local-decision domain, which is bounded above by a circular sensor range, to identify its neighbours and compute its movements. Each glowworm selects a neighbour that has a luciferin value more than its own, using a probabilistic mechanism, and moves toward it. That is, they are attracted to neighbours that glow brighter. These movements that are based only on local information enable the swarm of glowworms to partition into disjoint subgroups, exhibit simultaneous taxis-behavior towards, and rendezvous at multiple optima (not necessarily equal) of a given multimodal function. Natural glowworms primarily use the bio-luminescent light to signal other individuals of the same species for reproduction and to attract prey.The general idea in the GSO algorithm is similar in these aspects in the sense that glowworm agents are assumed to be attracted to move toward other glowworm agents that have brighter luminescence (higher luciferin value) [14].

Chapter 3

Butterfly:A new source of inspiration

Many more algorithms found place in the field of Optimization based on the behaviour of bacteria, bats, honey bees etc. Now, this made us to think about finding a species of our interest which can inspire us and help in deducing a meta-heuristic process which is aimed to solve engineering problems in a more simplified way. "Our attention was then driven towards a little creature, moving swiftly, flashing its beauty and colourful wings. When studied deeply, we understood that the bizarre flights it takes do mean something and this made us to focus further on its behaviour and finally to this work. That little creature is nothing but the well known BUTTERFLY".

3.1 Butterfly life cycle

Butterflies belong to the order Lepidoptera [15]. In Greek, "Lepidos" means scales and "ptera" means wing. Lepidoptera is a very large group; there are more type of butterflies (about 28,000 butterfly species worldwide) and moths than there are of any other type of insects except beetles. Butterflies have large, often brightly coloured wings, and conspicuous fluttering flight. Butterflies have the typical four-stage insect life cycle.Winged adults lay eggs on the food plant on which their larvae, known as caterpillers,will feed.The caterpillers grow, sometimes very rapidly, and when fully developed, pupate in a chrysalis.After the completion of pupa state, the pupal skin splits, the adult insect climbs out, and after its wings have expanded and dried , it flies off .

FIGURE 3.1: The Algais-Io-Butterfly

The stage from an egg to a butterfly outcome (life cycle) is called Metamorphosis. Some butterflies, especially in the tropics, have several generations in a year, while others have a single generation, and a few in cold locations may take several years to pass through their whole life cycle. Most adult butterflies live only a week or two, while a few species may live as long as 6-18 months. Female butterflies would always choose efficient mates to get higher nutrient values from them so that the inbreds would have good strength to live and to mate further.The choice of mate is done through communication among various butterflies.

3.2 Communication Strategies of Butterflies

Communication in butterflies is mainly for mating due to their short life span. Communication can also happen between the predator and the butterfly in which the butterfly

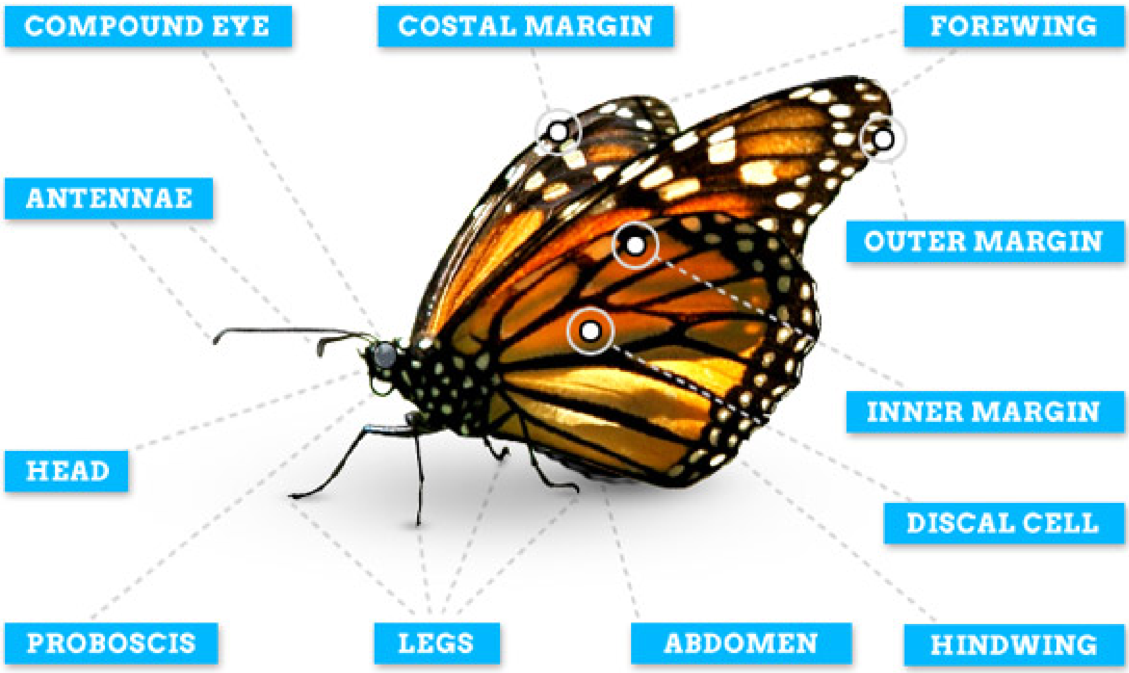


FIGURE 3.2: Anatomy of Butterfly.

tries to misguide the predator by camouflaging or hiding its bright colours. Patrolling and perching are the main mate locating behaviours of a butterfly and a brief description of two behaviors is given below.

3.2.1 Patrolling

In patrolling, the male butterflies are mobile and fly continuously in search of female butterflies until they find a female with acceptable colour and odour in their respective patrolling sites. In this, the male butterflies use UV light to recognize females of their own species based on UV reflections and wing patterns also [16]. If females are closer in distance to males, males use an additional method of releasing pheromones for the female to sense. If that does not affect female, male further approaches female by butterfly dances and flushes pheromones to the female antennae.

Patrolling species usually mate throughout the habitat at any time of the day, in high density conditions and where the habitat is large. The Figure 3.1 shows the pictorial representation of patrolling behaviour where in the attracting factor is the colour and UV reflectance among the butterflies.Patrolling may be beneficial in cold habitats where

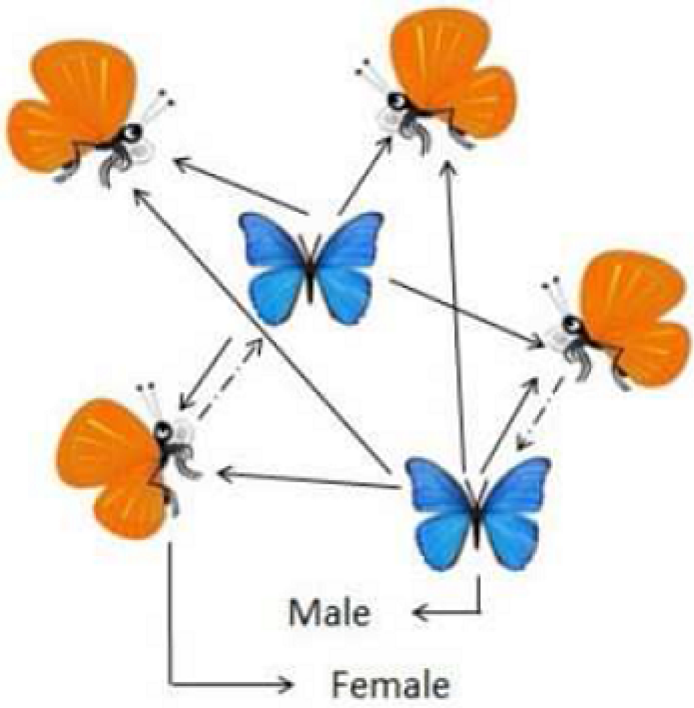


Figure 3.3: Pictorial representation of Patrolling.

flight may attend as a heat gain approach. Patrolling is not constrained with respect to area of habitat hence it is nonterritorial. In patrolling, the female must have to fly a certain distance to find the mate unlike perching where the male finds its mate. The species undergoing patrolling behaviour are Parnassius phoebus, Eucholes Ausonides, Hypayurotis Crysalus etc.

3.2.2 Perching

In perching, male butterflies are mostly immobile. They spend a long time sitting on the prominent leaf or hill top and survey the female butterflies passing by. The main attracting parameters are size and movement of the female butterfly. Perching species usually mate during one part of a day in limited area of habitat, hence it is territorial and occurs in less density conditions. This is because perching males often return to a place near the previous site after investigating a passing female [17]. The cost of territorial behaviour is perhaps less than that of patrolling because the territorial flights are shorter than the patrolling flights.

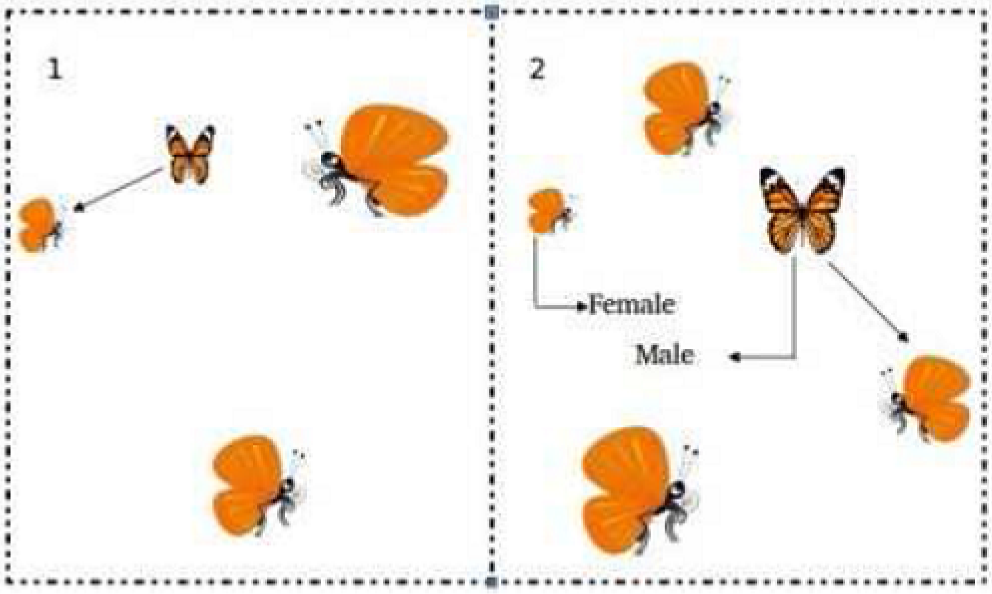


FIGURE 3.4: Pictorial representation of Perching.

The males in perching species have good ability to manoeuvre and accelerate; also they have higher body mass ratios, higher wing loadings and higher aspect ratios than patrolling species. When proper territorial sites are limited, males that have failed to achieve a territory adopt a patrolling strategy instead [18]. This perching behaviour is observed in species like Hipparchia semele, Hypolimnas misippus, Aglais urticae etc. Figure 3.2 shows the pictorial representation of Perching where in the attracting parameter is the size of the butterfly. The boundaries in the figure can be modelled to as perching sites.

3.3 Important Traits in Selection of mate

Pheromones: Butterflies use Hair Pencils to release a kind of scent called Pheromones. It is a strong attracting parameter and is released during courtship when the male fans or claps its wings and touches the antenna of the female butterfly. The olfactory receptors in the antenna of the female receive the pheromone as they have higher antenna sensitivity. These pheromones are also responsible for male-male competitions in defining their mating territories. Mate choice through pheromones is a close range response (less than a few meters), long distance pheromones is rare.

Butterfly size: In the early mating season, larger females mate with the larger males and smaller mate with the smaller males. Larger and symmetrical males are more attractive to females as the secretions produced by the male during courtship are proportional to its size. This is found in Danus Plexippus, Monarchs etc . In species like Bicyclus Anynana, normally sized males display higher mating than the ones with large hind wing and small fore-wing or vice-versa.

Colour: Colour of the butterfly can be either of the two possibilities; pigmented or structural colour. The structural colours due to the microscopic structures present on the lamella of the butterfly wings cause iridescence that is useful in communication. As the light falls at different angles on the butterfly wings, iridescence causes the changes in colour for different angles of viewing. It is virtually in UV region but some species have a blue peaking iridescence. Iridescent coloration is also an intra-specific communication signal that flashes on and off during flight. Such bright flashes of colour could also be used as predator deterrent signals.

UV reflectance: UV reflectance in butterflies has special significance in mating signalling. The butterflies consist of series of marginal eye spots on both the dorsal and ventral wing. The eye spots on the ventral wings play a role in predator deflection and that on dorsal fore-wing play a role in sexual selection . The female butterflies are also choosy towards the ones with the pupil of the eye spot visible it reflects UV light. However they prefer the mate with average sized pupil to the one with enlarged pupil size. The females can detect the differences between the males with varying UV pupil reflectance patterns and hence males with brighter pupils are more attractive. In some species like sulphur butterflies, male and female butterflies only differ in UV region; where the males being strongly UV reflective and the females non-reflective in UV .

Vision: Butterflies have a vision of 360o due to their compound eyes called as Omnivision. Its range is about 1 cm to 200 meters. In omni-vision, the image a butterfly sees is in the form of mosaic . It can also see the direction in which the electric field of a beam of light is oscillating (polarized light). Butterfly is extremely efficient at detecting movement but cannot focus its vision; hence what it sees is only a blur. Butterfly receptors can only perceive higher colour frequencies and hence are blind to red .

After studying in detail about the principal ways of different communication strategies viz patrolling, perching along with traits used, in the next chapter, the algorithm based on the butterfly communication strategies is presented with detailed explanation.

Chapter 4

Butterfly Paradigm for Multimodal Optimization

4.1 Butterfly Mating Optimization(BMO)

So far we discussed the patrolling and perching behaviour of butterflies in search space.we have seen the important traits in selecting the mate.A detailed explaination of Butterfly Mating Optimization is given below.

4.1.1 Description of BMO

As mentioned in section 3.1.1, in Patrolling, butterflies use UV reflectance (by males) and absorbance (by females) mechanisms based on distance i.e., when a male reflects some UV , the females nearby receive more share when compared to the farthest females [19]. This proposed "Butterfly Mating Optimization" assumes that there is no differentiation among males and females and every butterfly reflects the UV it has got and absorbs UV that it receives from all the remaining butterflies. Here, the reflection and absorption process is done in parallel. Hence this algorithm suggests a meta-butterfly model which replaces "Butterfly in the natural environment" with "Bfly in the search space".

BMO aims at solving multimodal optimization problems. In this each Bfly chooses its mate anywhere in the search space adaptively in each iteration which may lead to localization and hence it is appropriate to call this mate as local mate i.e. l-mate. This adaptive selection process of l-mate plays a key role in the BMO algorithm.Our algorithm starts with well dispersion of Bflies on the search space randomly. Then each Bfly updates its UV , distributes to and accesses UV from all the others, chooses l-mate and moves towards that. This algorithm description has been given below:

1.UV Updation Phase

In this phase UV of each Bfly is updated in proportion to its fitness value at the current location of Bfly as given below.

$$UV_i(t) = max\{0, b1 * UV_i(t-1) + b2 * f(t)\} \tag{4.1}$$

Irrespective of the reflectance and absorbance of UV of a Bfly, the UV is updated at time index 't', giving more importance to the current fitness and less to the previous UV , similarly choosing the b1, b2 values such that$0 \leq b1 \leq 1$ and $b2 > 1$.

2. UV Distribution Phase

In this phase, every Bfly distributes its UV to remaining Bflies such that the nearest Bfly gets more share than the farthest one. To distribute in this way, the following approach has been followed: For an i^{th} Bfly having UV_i reflects it to the j^{th} Bfly at a distance d_{ij} which is given by:

$$UV_{i \longrightarrow j} = UV_i \times \frac{d_{ij}^{-1}}{\Sigma_k d_{ik}^{-1}} \tag{4.2}$$

where i = 1, 2, . . . ,N; N is the number of Blfies; j = 1, 2, . . . ,N and j = i;$UV_{i \longrightarrow j}$ is UV absorbed by j^{th} Bfly from i^{th} Bfly; d_{ij} is euclidean distance between i^{th} and j^{th} Bfly; k = 1, 2, . . . , j, .,N and k = i; N is number of Bflies;d_{ik} is euclidean distance between i^{th} and k^{th} Bfly.

3. *l-mate* Selection Phase

If a Bfly chooses another Bfly which has maximum UV as its l-mate and later moves towards it, this leads to a rendezvous of all Bflies to a single peak. Here we consider an assumption that multimodal function profile (i.e., no of maxima and minima) is not known in prior. So, if the l-mate choosing process is made adaptive, it may lead all Bflies to form into disjoint groups. Keeping this in view, BMO proceeds with following approach of l-mate selection.

Initially an i^{th} Bfly arranges for itself all the remaining Bflies in descending order based on the amount of UV 's it has received from them. Now, if i^{th} Bfly chooses 1^{st} Bfly of this order as its l-mate, it moves towards that. Similarly all the remaining Bflies follow the same process in selecting their l-mate and take a move towards their respective l-mates. This behaviour will certainly lead to some kind of localizing atmosphere and sensing of peaks which can be seen clearly from the simulations depicted in the next sections. But to capture peak locations simultaneously an i^{th} Bfly should also consider the UV of remaining Bflies by sequentially comparing UV_i with UV of remaining Bflies arranged in descending order as mentioned above and it chooses the first encountered Bfly which satisfies the following condition as its l-mate.

$$UV(i^{th}Bfly) < UV(j^{th}Bfly) \tag{4.3}$$

where i = 1, 2, . . . ,N; j = 1, 2, . . . ,N , $j \neq i$ The above mentioned UV distribution, l-mate selection phases can be understood form the following illustration.

It explains l-mate selection of Bfly-1 among Bflies - 2, 3, 4. From the Figure 3.3, we observe that the Bfly 1 is at a distance of 4, 5, 2 from Bflies 2, 3, 4 respectively and absorbs UV in the indicated directions. Figure 3.4, shows UV values of all Bflies and the UV absorbed by Bfly-1 from them according to Eqn.3.2. As discussed in l-mate selection phase, the Bfly-1 arranges the descending order as [4 2 3] and sequentially compares its UV1 with UV 's of 4, 2, 3 as per the Eqn.3.3 and ultimately found Bfly-2 as its l-mate. Here, Bfly-1 didn't choose Bfly-4 as its l-mate inspite of it being the first one in the descending order because it has less UV when compared to it. This inducted an adaptability of l-mate throughout all the iterations.

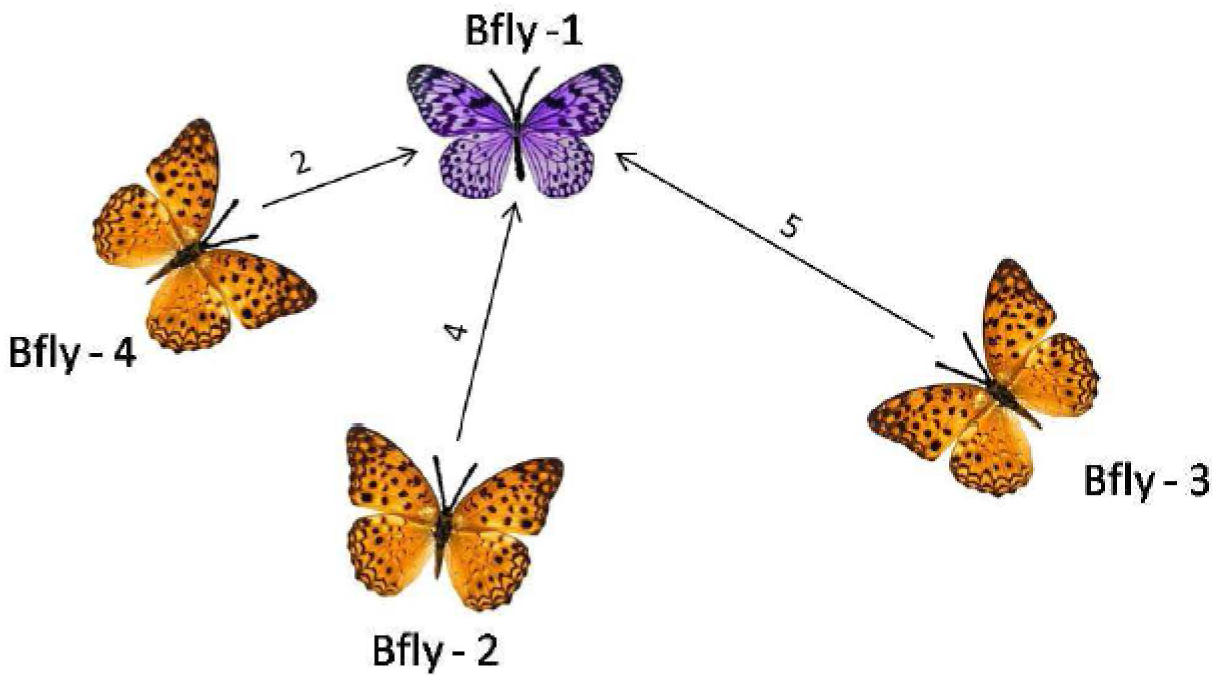


FIGURE 4.1: Pictorial representation of UV absorbance.

Property	Bfly-1	Bfly-2	Bfly-3	Bfly-4
UV_i	13	14	8	12
$UV_{i\rightarrow 1}$	–	3.684	1.68	6.315

FIGURE 4.2: UV values of all Bflies and UV absorbance values of Bfly-1 from Bfly-2, 3, 4

4. Movement Phase

Each Bfly is moved in the direction of its l-mate according to Equation

$$x_i(t+1) = x_i(t) + B_s * \frac{x_{l-mate}(t) - x_i(t)}{ceil(x_{l-mate}(t) - x_i(t))} \tag{4.4}$$

where B_s is Bfly step size;$x_i(t)$ is the position of i^{th} Bfly in a time index t. The pseudo code for the BMO algorithm is given below.

4.1.2 Pseudo code for BMO

pseudo code for Butterfly Mating Optimization

Randomly initialize Bflies;

$\forall$ i,set UV_i=$UV(0)$;

Set maximum number of iterations = $iter\_max$;

Set $iter$ = 1;

while ($iter \leq iter\_max$) do:

for each Bfly i do:

UV Updation; % using Eqn. 5.1

UV Distribution; % using Eqn.5.2

for each Bfly i do:

Select *l-mate*; % using *l-mate* selection phase

Update position; % using Eqn. 5.4

iter=iter+1;

Chapter 5

BMO Validation for Multimodality Functions

Multimodal functions are functions with availability of multiple good solutions.This solution set includes the presence of local optimas where local optima is the better value among its neighbour values.Multimodal optimization is different from local optimization in which the goal is to find the best feasible solution among all possible solutions and all secondary solutions are not concerned.

5.1 BMO for 3-peaks

5.1.1 For Static Search Space

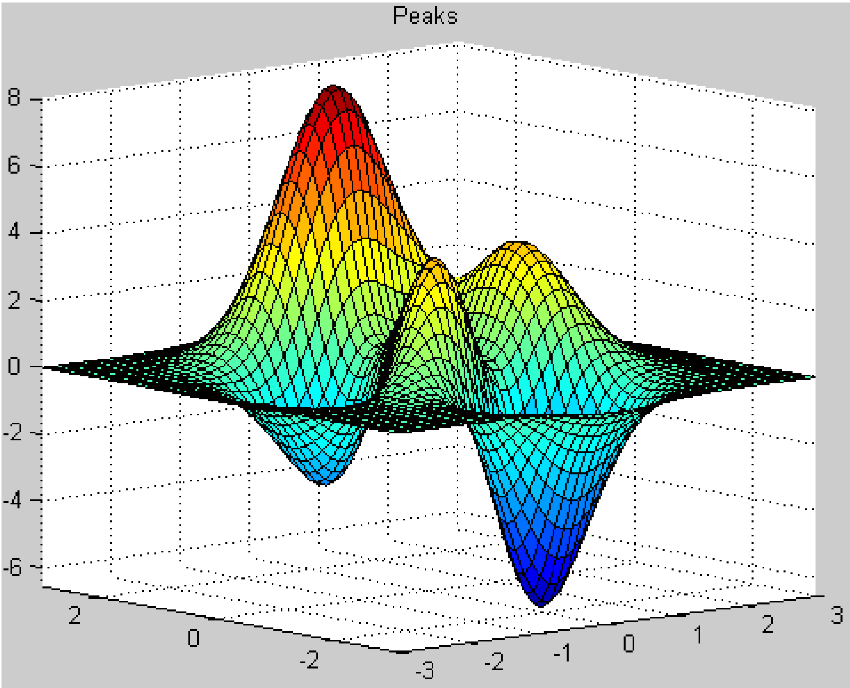


FIGURE 5.1: The 3-peaks function

The 3-peaks function has three peaks and two values.The BMO is aimed at capturing all the three peaks which are located at (0.06,1.625),(-0.45,-0.55),(1.35,0.05).The equation governing the 3-peaks function is given below:

$$f(x,y) = 3(1-x^2)e^{-[x^2+(1+y^2)]} - 10(\frac{x}{5} - x^3 - y^2)e^{-[x^2+y^2]} - \frac{1}{3}e^{-[(1+x)^2+y^2]}$$

First of all the bflies are randomly distributed in the search space.The number of bflies are our choice.

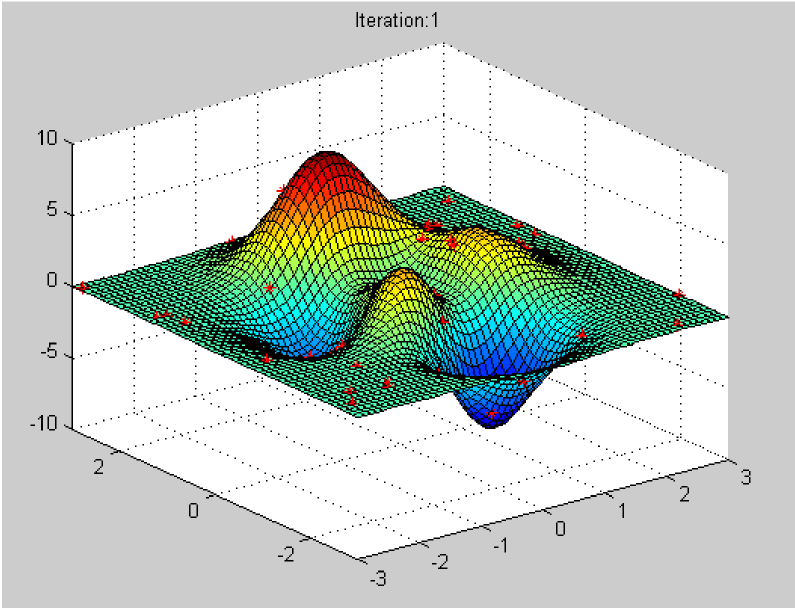
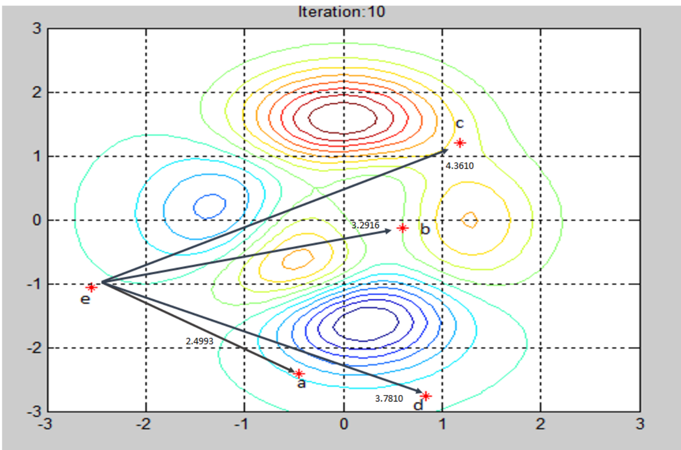


Figure 5.2: Random distribution of bflies

Now each bfly calculate the distance between its location and remaining bflies and distribution of UV is done through the distance based criteria in which nearest bfly receives more UV than the bfly which is far.This is done using equation 4.2.Now each bfly sort the received UV values in descending order and select the mate using equation 4.3.



After selecting the mate each bfly move towards its mate using equation 4.4. All these steps repeated in every iteration and after some number of iterations they will find all the peaks .The given below are the pictures at different iterations:

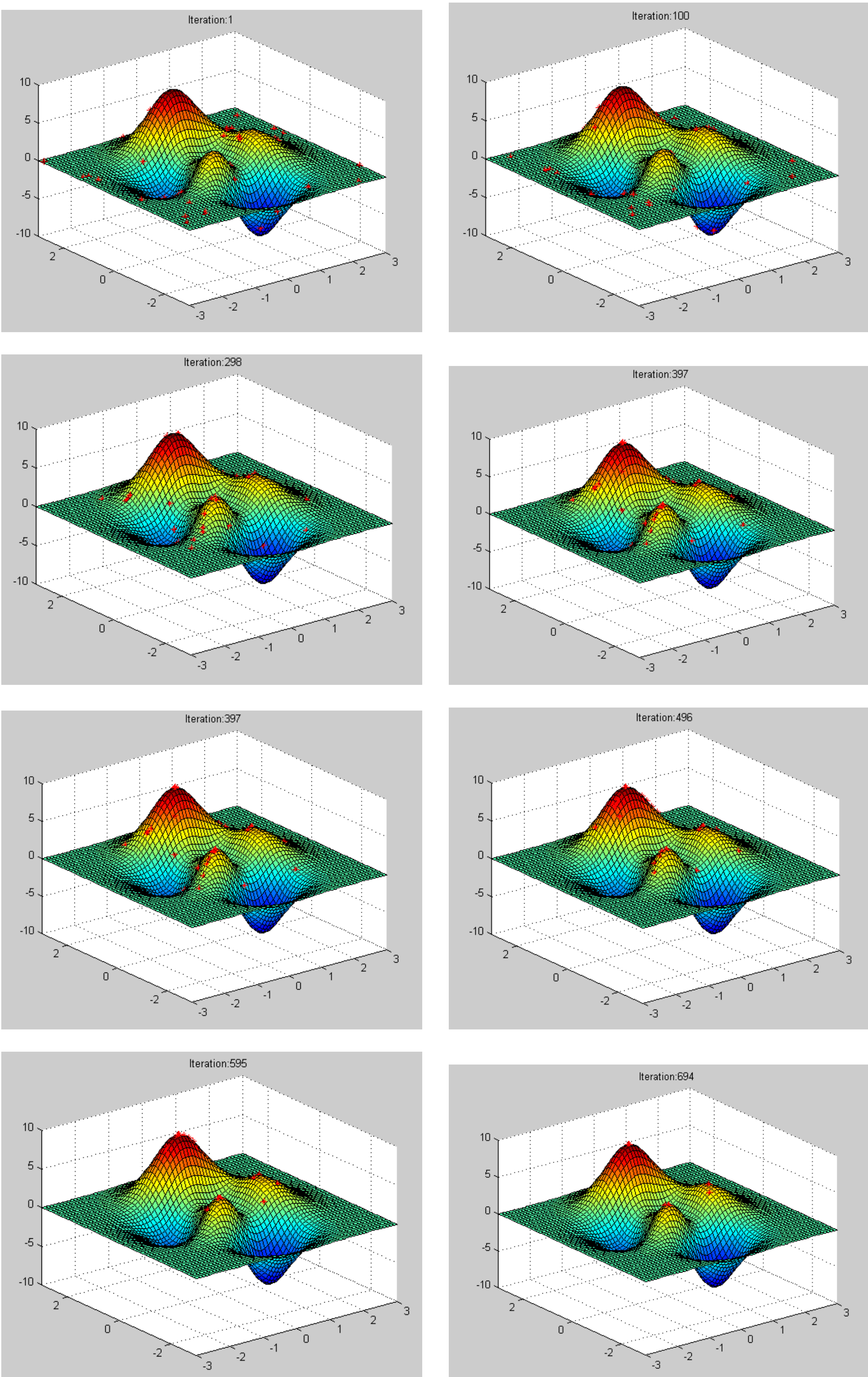


FIGURE 5.3: Plots at different iterations

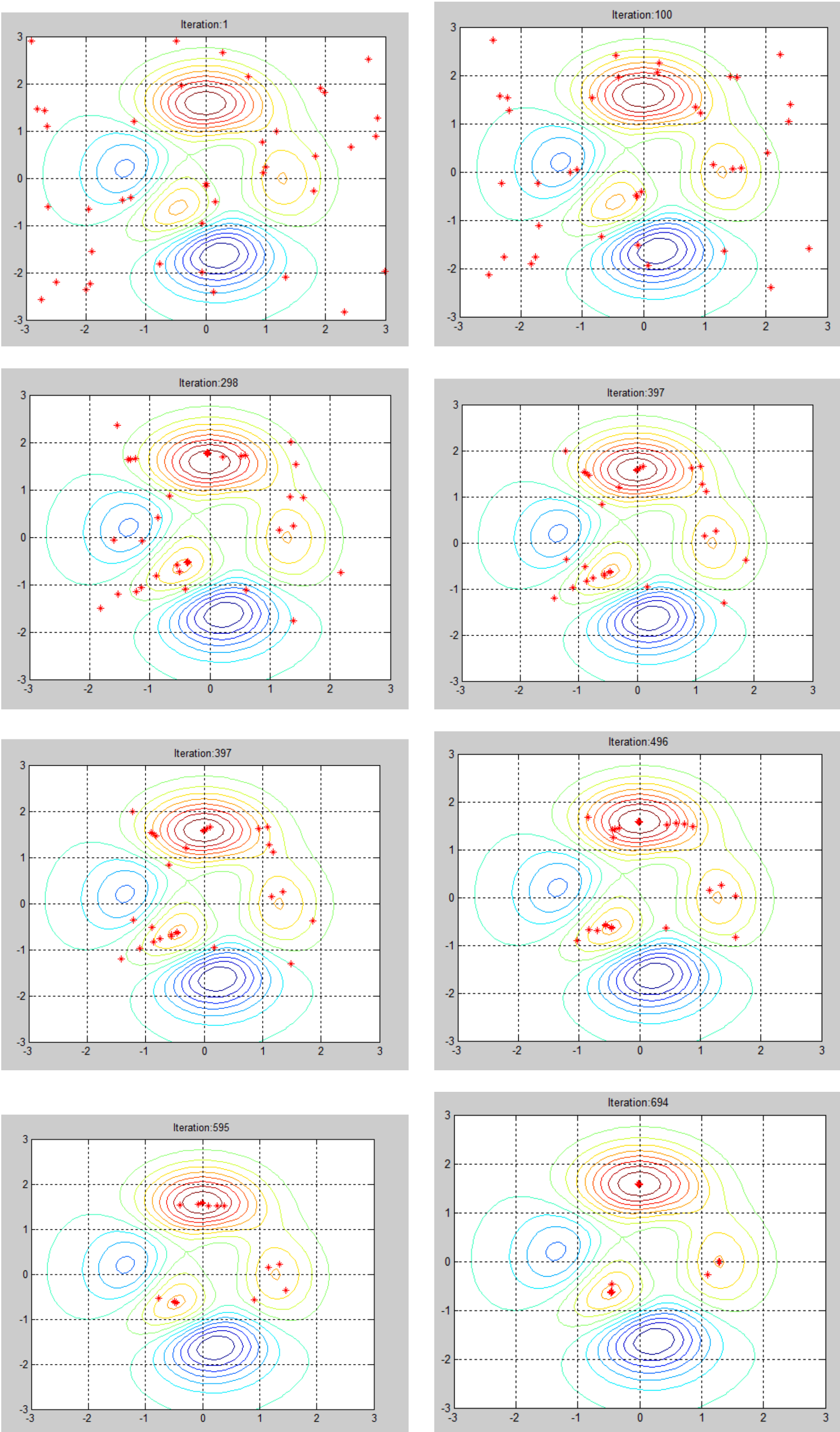
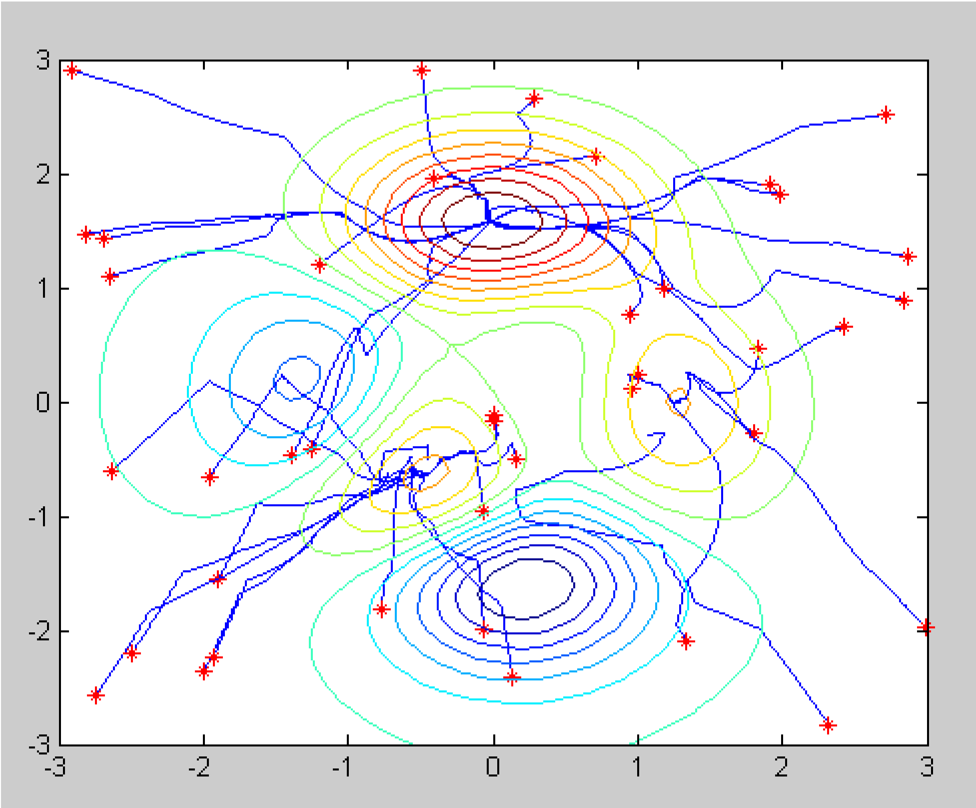


FIGURE 5.4: Contour plots at different iterations

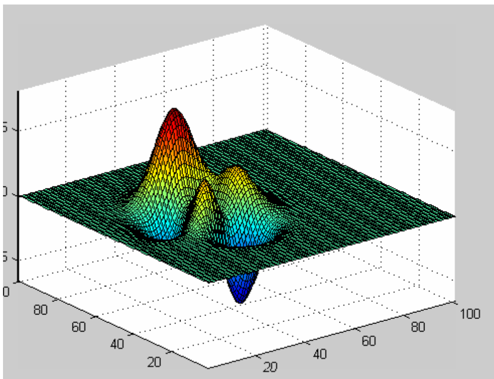
We can track the trajectory of each bfly from its initial position to its destination throughout the entire process.The given below picture show the trajectory of each bfly:

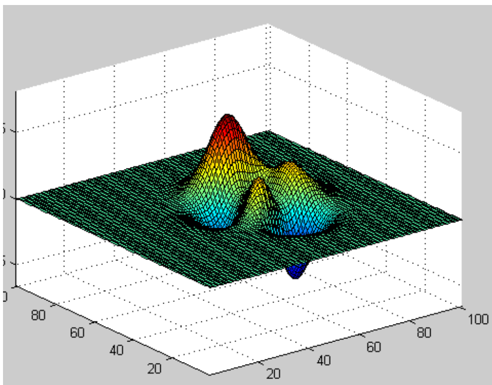


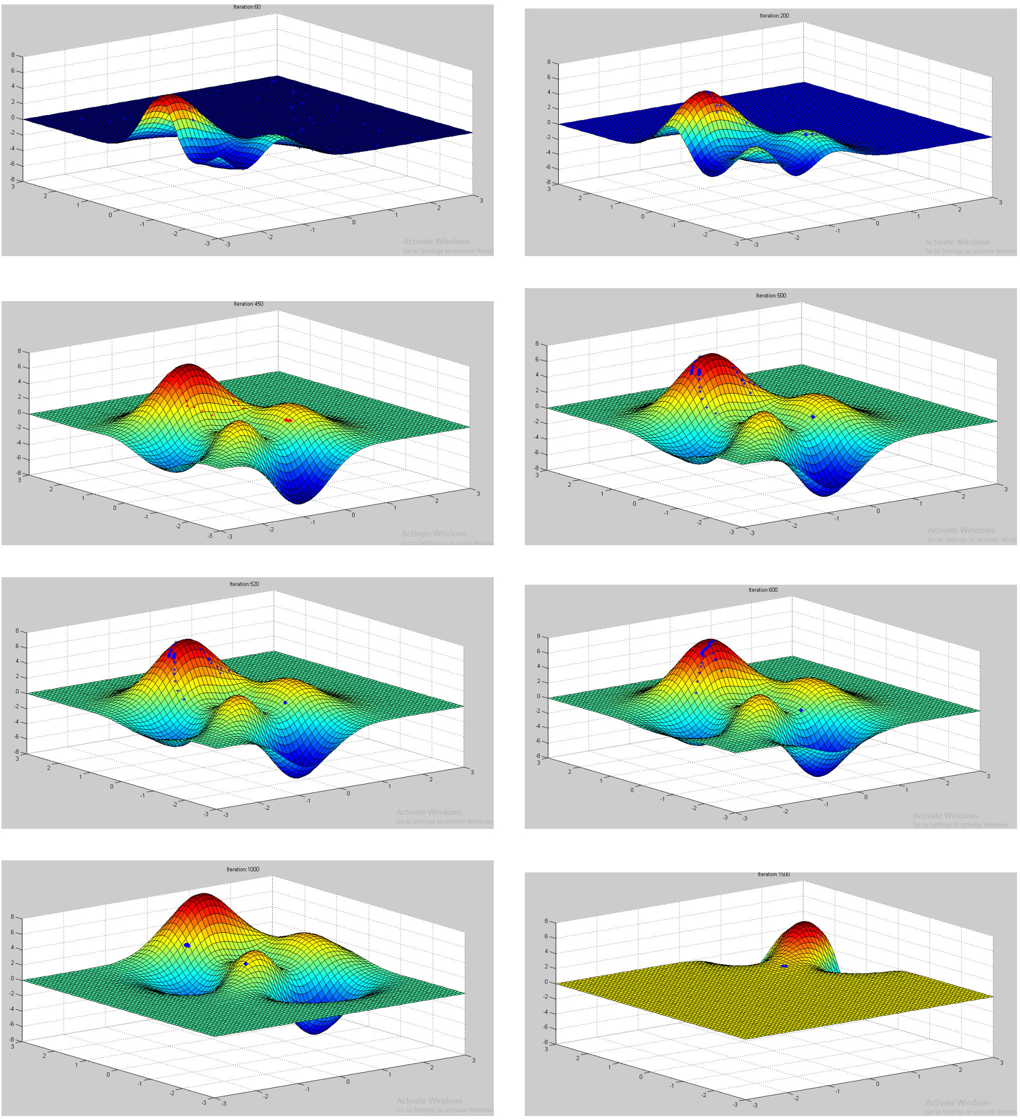
[ht]

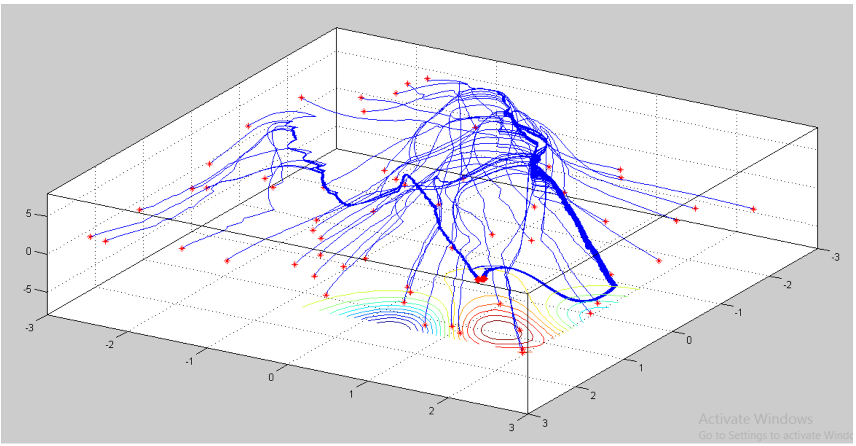
5.1.2 For Dynamic Search Space

If the given search space(3-peaks function) is varying continuosly then also we can capture the peaks . Simulations at different iterations were presented below:









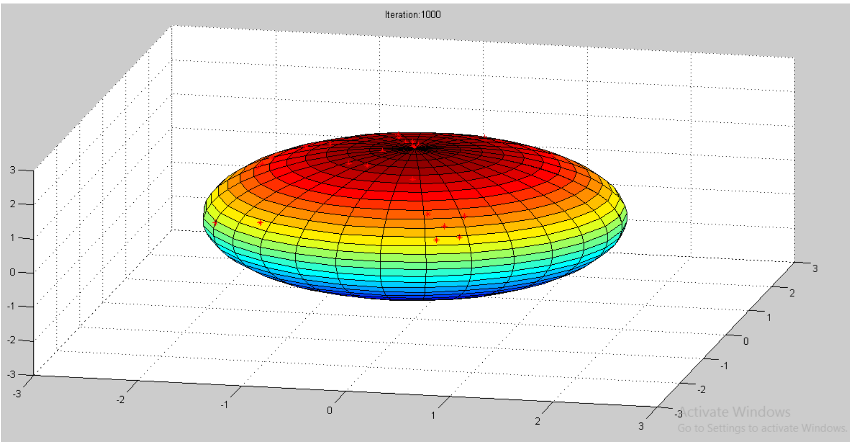
5.2 BMO for Sphere

The equation of spehre is given below:

$x^2 + y^2 + z^2 \leq r^2$

where x,y,and z are co-ordinates of the point and 'r' is the radius.

Our algorithm starts with random distribution of bflies over the surface of sphere.The bflies then find the distances between among them and distribute the UVs according to equation 4.2. Then each bfly select the appropriate mate and move towards it by some step size given using 4.4.All these steps are repeated in each iteration and they will finally converge at high peak. Here Sphere has only one peak so they will find the highest peak.



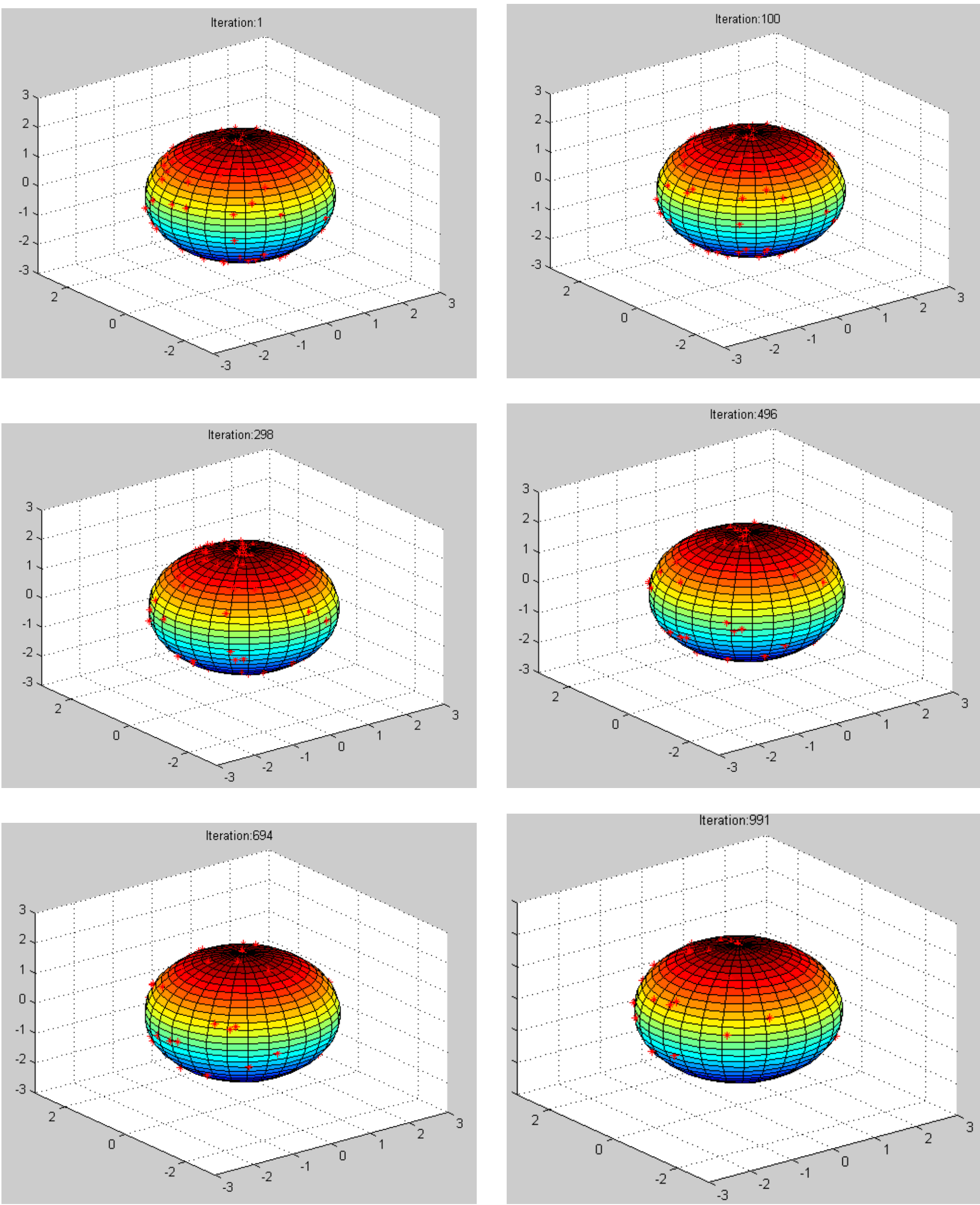
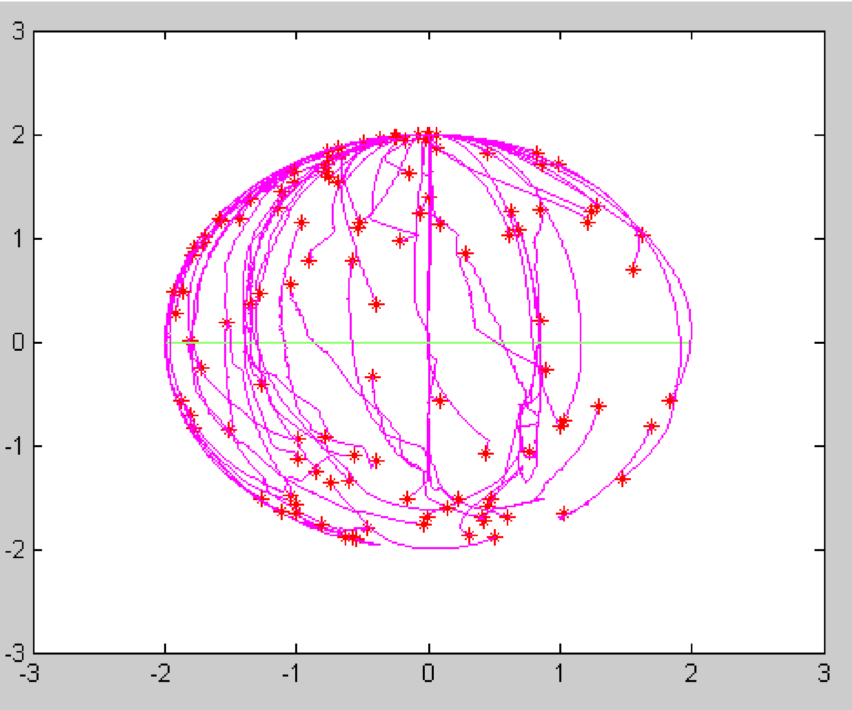


FIGURE 5.5: Plots at different iterations


3
2
1
0
-1
-2
-3
-3
-2
-1
0
1
2
3

Chapter 6

Conclusions and Future works

6.1 Conclusion

In this project, we followed a novel optimization method "Butterfly Mating optimization" (BMO) algorithm that can be applied to multimodal function optimization problems where the objective is to capture all the multiple optima in a given multimodal function.Here we used 3-peaks function and sphere as search spaces.The Bflies behaviour has been observed for static and dynamically varying 3-peaks function , for static condition of sphere. Initially, the need for multimodal functions has been discussed followed by the study of previously existing related work. We presented the development of BMO algorithm based on the patrolling behaviour of Butterflies that can be used for simultaneous capture of multiple optima of multi-modal functions.We described the notion of an l-mate selection phase, and the phases involved in the implementation of the basic BMO algorithm.

6.2 Future Work

In future, there is a scope to work on the following proposals: Consideration of other attracting traits of butterflies and using them in the algorithm; Mathematically proving the UV convergence of Bflies and explaining the formation of disjoint groups clearly; Analysing the parameter variation (no. of agents, no. of iterations, step size) and also the comparison of BMO and other existing algorithms; Clearly analysing the 'queuing' of Bflies while reaching the peaks; Application of BMO to higher dimensional search spaces; Application of BMO to signal source localization by either mobile robots or flying vehicles which can mimic the behavior of Bflies in BMO; Application in soft computing field for data clustering and classification etc. Finally this algorithm shows good potential as an alternative in the field of multi-modal optimization algorithms.

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