Robust approach for optimized path selection in Monarch Butterfly Optimization

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Abstract:
Nature Inspired Computing or (NIC) strives to develop new computing technologies by observing how nature can inspired to solve complex problems under various environmental conditions. This has produced unconventional research in new fields such as neural networks, swarm intelligence, evolutionary computing, and artificial immune systems. NIC technology is used in almost every branch of physics, biology, engineering, economics and even management. In this paper, one of the nature-inspired approach namely Monarch Butterfly Optimization (MBO) is used for modifying the chromosome parameter in it. The new conditional path selection criteria are developed for the movement of individual subpopulation along with the amplitude parameter. Ackley function is implemented by using conditional path selection mathematical model and the effect of amplitude parameter with adjusting ratio has been identified. The results show better performance among the conditional path selection criteria in terms of route optimization selection.

Keywords: Monarch Butterfly Optimization, Ackley function, Nature Inspired Computing, Conditional Path Selection Criteria.

Introduction:
(NIC) Nature-Inspired Computing aims to develop novel and innovative computing technologies by taking inspiration from naturally occurring phenomena to solve complex problems. These complicated issues are related to computing in a variety of environmental conditions. A powerful mechanism or field that can be used. Very applicable in areas such as NIC access technology, engineering, physics, biology, agriculture, and education. Science is a part of nature. Therefore, you can solve the NP-hard problem directly or indirectly with the help of natural processes. These are basically divided into several categories mainly Swarm Intelligence (SI) based approaches, Bio-Inspired computing-based approaches and Evolutionary computing-based approaches. A lot of the researcher have shown interest in these fields.

Swarm-based computing approach comes from imitating nature. It works with socially crawly swarms, such as ants and bees, and with more comprehensive knowledge than any individual in the swarm. Swarm is therefore a very successful and critical thinking group that can manage individual losses and at the same time offers a very attractive ability to countless people. Dorigo et.al [1] discussed about Ant Colony Optimization which is inspired by the foraging behavior of ants. Stephen et.al [2] discussed about ant colony optimization algorithm and some other algorithms, such as ant system, ant colony system, Max-Min ant system, rank-based ant system and other ACO variants. Max-Min Ant System performs only for best solution which helps to increase the pheromone during trials updation Nayyar et.al [3]. Based on the
behavior of fireflies, including the way they set fires and attract mates, demonstrated the solution to the extreme optimization problem Yang [4]. Particle Swarm Optimization (PSO) converges first which causes problems like local optimization because of premature capability Mei-ping song [5]. PSO is based on the flocks of birds which search food either in the form of groups or scatter themselves. Hemlata et. al [6], in the research work implemented PSO using single and multi-objective function. Based on the migration behavior of eel’s, EEL’s Algorithm is proposed which relies on three main aspects of eel: adaption of the environment, learning from neighborhood and sex mutation Sun et.al.[7] inspired from the behavior of cuckoo birds. These birds lay their eggs in other birds’ nest because they lack the use of bringing forth. Grey-Wolves optimizations follows a different approach where they follow leadership methodology [8].

Non-SI approaches which are not inter-linked are known as Bio-inspired non-SI approaches. Xin-She Yang et. al [9] proposed a flower pollination approach. Japanese tree frog calling algorithm in which female frogs get attracted by the calls of male frogs Hernández et. al. [10].Dolphin Echolocation Algorithm provides solution for power dispatch issue to solve the optimization problem [11]. Based on the food finding method of fishes, Fish School Search Algorithm is proposed [12]. Sung Hoon Jung et. al.[13] proposed a queen bee evolutionary approach which is important for the life cycle of reproduction. Brain Storm Optimization Algorithm [14] is based on the human brainstorming method when encountered with some kind of problem. Inspired by nature, a new Shuffle-Frog leaping algorithm (SFLA) is introduced by [15]to analyze combinational optimization issues.

Evolutionary computing is part of a global optimization algorithm inspired by biological and genetic evolution. The necessary set of solutions related to the biological world have undergone artificial or natural selection and mutation. Gradually, the population will evolve towards adaptation, which in turn will help select the suitability features of the algorithm. Evolved computing technology is gaining popularity in the computing world, providing optimized solutions for a variety of computing problems. Holland JH discussed about Genetic Algorithm [16]. Based on the specific mutation sizes, Daan Wierstra et. al. [17] proposed an Evolution Strategy Algorithm. Differential Evolution Algorithm claims that instead of traditional crossover or mutation, new offspring may be created from parent chromosomes. It may be used to keep track of a population of potential solutions for optimizing an issue [18]. Genetic programming is an evolutionary learning method that can be widely used in the computing industry for classification. As an empirical approach to evolutionary computation, this technique can be used to represent complex patterns such as trees. A computer program is encoded as a collection of genes and then altered to create the most suitable gene in the form of a computer program [19].

Based on the Physics and Chemistry concepts, GbSA-MLT also known as Galaxy-based search algorithm has been proposed enhancing the multi-level threshold of the galaxies [20], Rabanal et. al [21] proposed a River Formation Dynamic Algorithm which has advantage of various ACO methods and along with it can be used for Traveling Salesman Problems. Based on the theory of the evolution of the universe, Big Bang Big Crunch is discussed by Erol et. al.[22]. A modified version of Big Bang Big Crunch(BBBC) is proposed where it takes more than one population into the consideration, PB3C. A new mechanism to search for the nearest shortest path using the existing PB3C for Routing in Wireless Mesh Network is discussed by Singh A et.al [23].

In this paper, considering Monarch Butterfly Optimization using the Ackley benchmark function, the chromosomal parameters were updated together with conditional path selection criteria for individual in
subpopulation. The performance of the modified Ackley function was compared based on the amplitude parameter and conditional path selection.

**Working of Monarch Butterfly Optimization:**

The Monarch Butterfly Optimization research is inspired by the movement patterns of butterflies. The technique is based on two main operators: Migration Operator and Adjuster. In the following legislation, the movement of monarch butterflies may be idealized to address several optimization issues.

1. All monarch butterflies only occur in Land 1 or Land 2. On other words, the whole population of monarch butterfly in Land 1 and Land 2.

2. The butterfly produced in Country 1 or Country 2 for each child is a monarch.

3. After a youngster is manufactured, an old butterfly monarch will migrate to preserve the population. With the MBO technique, it may be done by changing your news if your parent is physically better than your parent. On the other side, if the newly formed person has no better condition with his or her parent, he or she is susceptible to be rejected. In this circumstance, the parent is kept alive and unstructured.

4. The monarchs of the butterfly with the highest fitness pass instantly and they cannot be adjustment by any operators. This ensures that monarchic butterfly persons continue to degrade in consistency or efficiency with an increase in generations.

5. For Monarch Butterfly Optimization Algorithm [24] the following chromosomal parameter for the initial population was utilized in the Ackley function.
Conditional path selection in Monarch Butterfly optimization:

The movement in Monarch Butterfly Optimization is stated in terms of the current global best individual, a random butterfly in subpopulation, and Lévy flight, which may be calculated by the adjusting ratio $p$ and BAR for individual $i$ in subpopulation (Butterfly Adjusting Rate). Figure 1 depicts butterflies’ subpopulations in a random population or search space. The usage of butterfly adjusting operator mainly considers three factors:
(1) The impact of the social model by advancing to the global optimum.

(2) The cognitive impacts of other butterfly’s by switching to a random individual.

(3) Use of Lévy flight to improve population variety and search scope. The following function is used to produce a new generation from subpopulation:

\[ P(x)_1 = ax^2 + bx + c \]  \hspace{1cm} (1)

If \( a = 0 \), then we have a linear \( P(x)_1 = bx + c \) path. Further for \( c = 0, P(x)_1 = ax^2 + bx \), the object passes through the origin of domain. Following are the different conditional path selection functions used in Ackley function for Monarch Butterfly Optimization algorithm (\( a = 1, b = 0, c = 0 \)). This function demonstrates the movement of butterfly randomly in the search space.

\[
P(x)_1 = \begin{cases} 
P(x)_{best} = x^2 & \text{if } \text{rand} \leq p \\
 x^4 \lor \sin(B\pi x) & \text{if } \text{rand} > p \land \text{rand} \leq \text{BAR} 
\end{cases}
\]

\[
\text{if } \text{rand} > p \land \text{rand} \leq \text{BAR} \{ \text{if } \text{RMSE for } x^4 < \text{RMSE for } \sin(B\pi x) \text{ then } P(x)_1 = x^4 \\
\text{else } P(x)_1 = \sin(B\pi x) \}
\]

\[ P(x)_2 = \cos(A_0\pi x) \]

1. The following chromosome parameter for initial population was used in the Ackley function for Monarch Butterfly Optimization Algorithm[24].

\[
\begin{align*}
\text{MinParValue} & = -30 \times \text{ones}(1,\text{OPTIONS.numVar}) \\
\text{MaxParValue} & = 30 \times \text{ones}(1,\text{OPTIONS.numVar}) \\
\text{Chrom} & = [\text{MinParValue} + (\text{MaxParValue} - \text{MinParValue} + 1) \times \text{rand}(1,\text{OPTIONS.numVar})]
\end{align*}
\]  \hspace{1cm} (2)

In this paper, we have modified the Ackley function used in Monarch Butterfly Optimization Algorithm[24]. In the Ackley function, the chromosome parameter is being modified as
The cost of each member in population is calculated by following function

\[
Chrom = \left( \left( \frac{MaxParValue - MinParValue}{MinParValue - AvgParValue} \right) + 1 \right) \times rand(1, OPTIONS.numVar)
\]

The result and discussion

Considering the working of Monarch Butterfly algorithm, the population space of butterfly is divided into subpopulation. Movements are represented by current global Best Objects, random subgroup objects, and Levy Flights. These can be calculated using the scale \( p \) of the subpopulation individual \( i \) and the butterfly adjustment factor \( BAR \). In this paper we have modified the conditional path selection criteria in Ackley function and chromosome parameter in MBO. Figure 2- Figure 3 demonstrates the results obtained by different variations in conditional path selection criteria with amplitude. Figure 2 explores the effect of amplitude parameter on the performance of Ackley function in MBO with optimal path \((x^2)\) and it was observed that for the random generated results, the better agreement in the minimum and average cost can be seen as the amplitude parameter enhanced from 0.5 to 2. The similar kind of performance was observed with the increase in amplitude parameter \( B \). Figure 3 shows the performance of Ackley function in MBO with another path \( x^4, \sin(B\pi x) \) and it is noticed that these are less optimal than with optimal path. Hence if rand is less than adjusting ratio \( p \) then the optimal path is considered in Ackley function else first the performance of another path say \( x^4 \) and \( \sin(B\pi x) \) is compared by computing the root mean square error and best is being selected with butterfly adjusting rate \( BAR \). As excepted the performance of exponential \((e^x)\) conditional path selection criteria in Ackley function in MBO is comparatively less accurate as compared with optimal path \((x^2)\) and \( x^4, \sin(B\pi x) \).
Figure 3 Performance of modified Ackley function in MBO with varying Amplitude
Conclusion

Nature Inspired Computer (NIC) aims to build new computing systems by exploring how natural events may handle complicated issues in a variety of environments. In this study, the chromosomal parameter is revised using a nature-inspired technique called Monarch Butterfly Optimization. Along with the amplitude parameter, new conditional path selection criteria are created for the mobility of subpopulations. Employing the Monarch Butterfly method, the population space of butterflies is segmented into subpopulations. The Ackley function was created using a mathematical model based on conditional route selection, and the influence of the amplitude factor on movement has been discovered. The migration is determined using the adjusting ratio p and butterfly adjusting rate BAR for community member as well as the current global best individual. It is concluded that the amplitude parameter affects the movement of butterfly during path selection. If the first best path is not obtained, then the movement is further optimized by comparing the best selection in terms of the minimum root mean squared error.

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