A Survey on Cat Swarm Optimization

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Abstract* — *In this paper biologically inspired metaheuristic Cat Swarm Optimization is reviewed. CSO evolved from the behavior of Cats is a promising algorithm for providing solutions to real-time applications. The study presents the CSO algorithm, variants of CSO, applications and future scope of CSO algorithm.

Keywords* — *Optimization, meta-heuristics, Cat Swarm Optimization

I. INTRODUCTION

Optimization is the study of planning, designing, and solving complex problems in day-to-day life in recent years. The optimization problems are of high significance in knowledge-based domain like scientific sector and economy
based domain like Industrial Sector. Right from vehicle logistics management to constraint job scheduling and from data repository integration, Vision tracking to NP-Hard Problem solving, optimization management is subjected to various constraints. The main objective in optimization is to optimize the physical parameter depending on the problem considered. In the past decade, the biologists to employ various Biological (or) Nature-Inspired Algorithms for solving almost endless array of real-time application. Hence the analytical performance of the mathematical model is simulated using diverse nature- conciliation.

This basic set of classification is again sub classified into various streams depending on two mechanisms, namely Guided/Non-Guided and Direct/Indirect. The examples of classical direct optimization techniques are Greedy search, Fibonacci Series, Golden Section Search, Nelder, and Mead, etc. Hill Climbing, Grammatical Systems, Evolutionary Systems, Social Systems, etc. are examples for guided probabilistic algorithms. Backtracking and Las Vegas falls under the classification of non-guided search techniques (1). Most of the biologically inspired optimization algorithms fall under the category of Monte Carlo (MC) algorithms. It is an essential classification of probabilistic algorithms (2).

Within the last decade, many heuristics became feasible for solving real-world problems. In this Paper, a review of Cat Swarm Optimization is discussed. The core description of CSO algorithm and its need for utilization in research are also stated. The various advantages and applications of Cat Swarm Optimization are also discussed.

The structure of this paper is organized as follows: Section 2 describes the literature review of CSO. Section 3 presents the algorithm. Section 4 the variants of CSO. Section 5 represents the applications and future Scope of CSO. Conclusions are drawn in the section 6.

II. LITERATURE REVIEW

Biologically Inspired Algorithms is a class of optimization technique which encompasses robust adaptation combined with machine learning astuteness. These algorithms are derived by captivating the stirring inspiration of the collective behavior and decentralized management structure of biological species. Studying the underlying individual behaviors by combining behavioral observations, the researchers and scientists have solved real life problems with mathematical or simulation modeling (3). Novel optimization techniques are proposed in past years due to strenuous research efforts, for the exploration and exploitation of solution sets with diversification and intensification. In most cases, the natural computation outperforms the traditional/standard optimization algorithms with the attributes of memory update and population-based search solutions.

The taxonomy of natural computing is classified into seven major categories as Stochastic Algorithms, Physical algorithms, Probabilistic Algorithms, Evolutionary Computation, Neural Networks, Social Systems, and Immune Systems (4). Although the stochastic, physical and probabilistic algorithms are classified under nature inspired algorithms by Dr.Jason Brownlee, these algorithms does not seem refined and bang-up with other categories of Bio-Inspired Computation. The Stochastic and Probabilistic algorithms use stochastic/probabilistic model of candidates, which lack in metaphor and an inspiring system. Yet, these algorithms form the basis for mathematical modeling, hybridization, refinement, neighborhood search procedure, iterative search, etc in advanced natural computing techniques.

The Evolutionary algorithms are developed from the mechanism of biological evolution. From 1950, the experimentation on evolutionary systems started. Gradually scientists developed Evolutionary Programming in 1966, followed by Evolutionary strategies, Genetic Algorithm, and Genetic Programming etc in the successive three decades. The main biological constituents of evolutionary computation are cell, chromosomes, genetics, reproduction and natural selection.

Based on the fitness function, data structure, mutation and crossover operator, selection of parents and children and termination condition the evolutionary algorithms can be designed. The different properties of metaheuristic techniques are incorporated to original Evolutionary Algorithms to form hybrid algorithms and variants of Evolutionary computation are developed to meet real time problems. Swarm based Genetic Algorithm, Adaptive GA, Fuzzy based Genetic Algorithm, Neural based Evolutionary Programming, Pareto Archived Evolution Strategy, Non Dominated Sorting GA and Differential Evolution with Swarm Intelligence, etc is few of the innumerable combinations of Evolutionary Computation paradigm in research arena. As the world of Evolutionary Computation is a “huge wave”, it is utilized in variety of domains. Some of the real world examples are; Short Taps Puzzle, Knight’s Tour, Travelling Salesman Problem (TSP), Tantrix, Cellular Encoding, Circuit Design, Edge Encoding for Graphs, Chemical kinetics, Mobile communications infrastructure optimization, protein folding, Quality control etc.

Artificial Neural Networks (ANNs) are developed to achieve biological system type performance using a dense interconnection of simple processing elements analogous to biological neurons (5). The history of ANN dates from early 1940’s. Since its inception, many research works were carried out. At present many hybridization/fusion algorithms are developed along with Evolutionary strategies, Fuzzy Logic and Swarm Intelligence. The best remarkable usage of ANN is to dynamically control the robotic parts by rat’s thoughts (6). ANNs have proven to be worthy of investigation in variety of automation problems like, self driving of a car, composition of music, automated recognition of signals and multidimensional objects.

Probabilistic algorithms do not assure the best solution in all scenarios. In particular, since they are fairly general search algorithms, it can be difficult to “fine tune” the algorithm to work well on any specific problem. Even though the Evolutionary Algorithms, Neural Networks and Immune systems seems to work quite well in practice, there are several limitations attached to them as well. The neural networks have certain limitations like, need of frequent training and supported parameters for operation, high processing time as complexity of the network is increased and the architecture is different from other hardware architectures and hence emulation is required. Though the immune systems have inspired many engineering solutions like, pattern recognition, self organization and distribution, AIS don’t move through the network nor work autonomously.

Even though the existing algorithms achieve promoting results for any class of problem, it is found inferior in certain aspects for long run towards any combinatorial problem. Several contemporary heuristic techniques have motivated several researchers to focus attention on the natural world and conceals the characteristics of different creatures in the development of optimization algorithms.

Swarm Intelligence is coined by Gerardo Beni and Jing Wang in 1989, in the context of cellular robotic systems (7). The design paradigm for these systems is fundamentally different from traditional approaches. Depending on the applications, reinforcement component that implicitly lead to better solutions, constriction and acceleration factors, inertia weight, position and velocity factors are chosen by the researchers.

As there are 84, 00,000 species in the world, developing heuristics from nature is an on-going and indefinitely long process. Moreover, the cognition inspired from nature is always long-lasting. This led and leads many researchers and scientists to adopt varied terminologies and advanced operators on natural selection and evolution, to achieve stability and convergence in Multidimensional Search space. It aids in solving non-linear, non-uniform, non-differentiable problems with minimal execution time. Correspondingly, many variants of swarm algorithms are proposed to avoid convergence towards local optima, premature convergence, and acquire improved performance. Similar to the original algorithms, the variants and advanced algorithms are also simple to implement and numerically robust. Monkey Search Algorithm, Cuckoo Search Optimization, Fire Fly, Bee colony Optimization, Krill herd Optimization, Shuffled Frog Leaping algorithm, Slime Mold Algorithm, Glowworm Optimization, Bat algorithm, Spider Algorithm, elephant Search algorithm, Grey wolf algorithm etc are some of the emerging nature inspired Computational Intelligent algorithms. Though, many of the algorithms are widely employed in diversified research areas, their true probable credentials is not yet utilized. One such algorithm is the Cat Swarm Optimization – an innovative computational intelligent technique, inspired by the felineness of fissiped mammals called “CATS”.

Cat Swarm Optimization adopts a swarm of cats to represent the potential solutions of an optimization problem. Cats are pet animals, which have unique behaviors and as a predator they survive and self-defense from enemies by their instinct alertness. In 2006, by analyzing the behavior of Cats, Shu-Chuan Chu, Pei-Wei Tsai, and Jeng-Shyang Pan, developed CSO algorithm (8). Cat swarm Optimization has similarity with PSO, but their search process differs from the viewpoint of inspiration, splitting up of population and sequence of execution. CSO can reach a diverse set of local optima solutions, instead of polarizing the entire population towards the best candidate solution.

CSO performs learning and multi-modal search through two processes, namely seeking mode and tracing mode. Cat Swarm optimization provides scalability and adaptability to varied real-time applications. The CSO algorithm is extremely parallel and presents a fine tractability in terms of computational time and cost.

Some of the advantages of CSO are; it is simple and it has high degree of parallelism. The algorithm can be combined with other optimization algorithms to form hybridized algorithm. CSO can be used to train neural networks, wireless sensor networks, production and automation systems. The applications of CSO include the following fields (8) :

- Machinery Fault Detection
- cooperative Spectrum Sensing of Cognitive Radio Networks
- Class room Response systems
- Multiobjective optimization (Chaos, Global Numeric Optimization and Unconstrained Optimization)
- Distributed systems (Task allocation, Project scheduling, Data Mining, Optimal contract Scheduling.. etc)

Many real life problems like voltage stability enhancement in Power systems, Aircraft Scheduling, Traveling salesman problem, Graph coloring problem, Image classification and distributed cloud computing employed Cat swarm Optimization to solve the multiple conflicting objectives. CSO have rendered near-optimal solution to these engineering and science problems. Cat Swarm Optimization is thus an efficient class of heuristics that are easy to hybridize with any class of application oriented algorithms.

III. CAT SWARM OPTIMIZATION

Cat Swarm Optimization was developed in 2006 by Shu-Chuan Chu , Pei-wei Tsai, and Jeng-Shyang Pan. Through inspecting the behavior of cat, the authors presented CSO as a novel algorithm of Swarm Intelligence (8). By amalgamating with two modes and user-defined proportion, CSO is formulated for solving multiobjective optimization problems.

Chu and Tsai (8) states that the artificial structure can be viewed as the model for modeling the common behavior of cats.

S.C. Chu et al; studied the behavior of cats and devised two sub-models namely 'seeking mode' and 'tracing mode'. By combining these two modes, CSO can be carried out for required problem to be solved.

- **Seeking Mode:** The cats are prone to rest, look around and seek the next position to move on.
- **Tracing Mode:** The cats have the tendency to crouch and wait, to attack its prey.

In order to obtain best optimal solutions in CSO, it is mandatory to perform certain operations over the swarm of individuals. In this section, the basic terminologies and operators used in CSO are discussed.

A. Solution Set:

The solution set is the key aspect of any optimization algorithm. As Cat swarm Optimization, deals with the behavior of cats, the algorithm is modeled by portraying cats as agents in the solution set. The swarm is initialized with a population of individuals – cats. The different parameters of

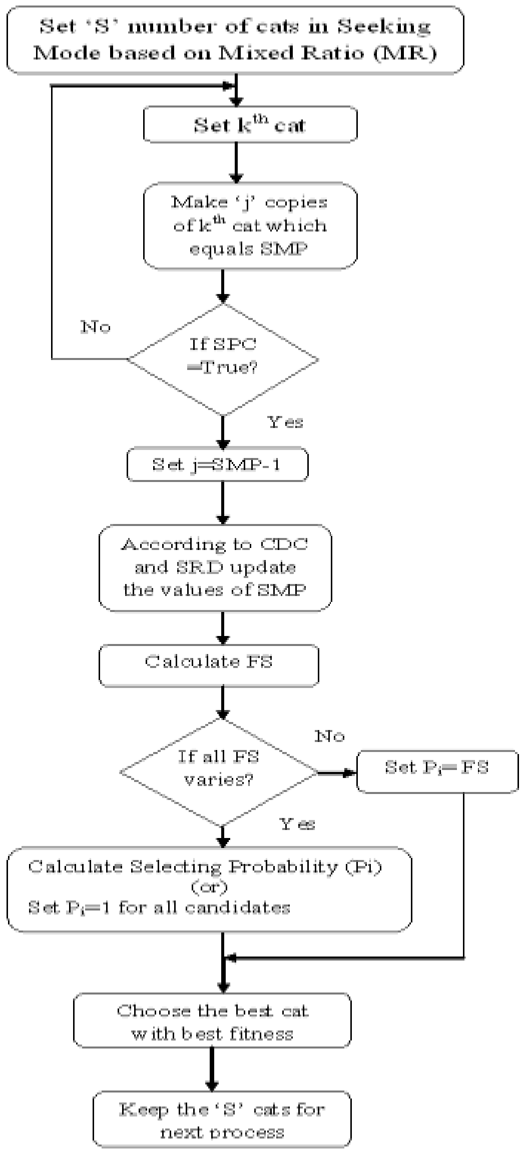

Figure 1: Seeking Mode of CSO

solution set are position of cats, velocity for each aspect, fitness value and flag.

B. Fitness Value and Fitness Function:

A group of ‘N’ Cats are chosen with ‘M’ dimensions. For each dimension, there is ‘f ’, a fitness value, which represents the accommodation of the cat to the Fitness Function ‘FS’. The fitness value plays an important role in making several decisions during seeking mode. The fitness function represents the goal of the optimization problem. In CSO, the position of best cats in memory is chosen as the fitness function.

C. Flag:

A flag ‘F’ is used to identify whether the cat is in seeking mode or tracing mode. The two modes are combined to define the sequence of the CSO algorithm.

D. Mixed Ratio:

It is defined as the ratio of number of cats in tracing mode to number of cats in seeking mode. The parameter MR is similar to random parameter (or) probability factor in other evolutionary techniques.

From the analysis of the structure of CSO, it is inferred that the individuals search independently in the seeking mode and they exhibit collective behavior in the tracing mode.

By updating the seeking mode and tracing mode, the reasoning capability of the state of period and the knowledge about velocity are determined. In turn, the positions of the cats are iteratively evaluated. After repeating this operation, for several iterations, the global optimum solution is sought.

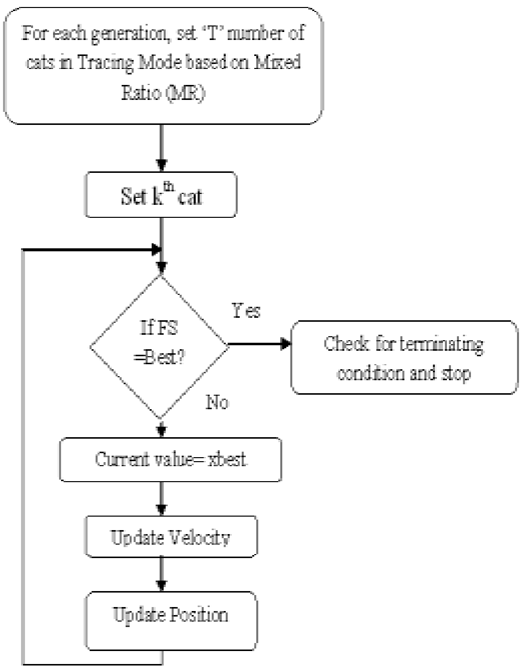

Figure 2: Tracing Mode of CSO

E. TEST FUNCTIONS FOR CSO:

To validate the characteristics of CSO, Chu et al; has applied CSO, into six test functions and the performance is compared with PSO and PSO with weighting function. The experimental results demonstrate the efficacy of the new metaheuristic Optimization. The usage of parameters for CSO, is listed in Table 1.

Table 1 - Parameter setting of CSO

Parameter	Value or Range
MP	5
SRD	20%
CDC	80%
MR	2%
c_1	2.0
r_1	[0,1]
ECH	20
No. of Groups (G)	2 to 4
Dimension	30
Population Size	16
Minimum iteration	500
Cycles/ Test Function	50

IV. VARIANTS OF CAT SWARM OPTIMIZATION

The various classifications of Cat Swarm Optimization like parallel CSO, Discrete Binary CSO, Enhanced CSO, Average inertia weighted CSO and so on.

Parallel structure of Cat swarm Optimization (9) is investigated by Ei-wei Tsai et al; in 2008. A good solution has some similar structures. This is the concept of proximate optimality Principle. The evaluation of each solution is carried out in a parallel mechanism in the tracing mode.

Adaptive Dynamic Cat Swarm Optimization (or) Average inertia weighted CSO (10) is developed by Meysam Orouskhani, Yasin Orouskhani, and Mohammad Teshnehlab. In order to alleviate the complexity of pure CSO and to improve the convergence accuracy level, the authors have incorporated adaptive inertia weight and adaptive acceleration coefficient to the velocity equation. Secondly, the authors have incorporated the information of two previous/next steps along with a new factor to form new position update.

Enhanced parallel cat swarm optimization (EPCSO) based on the Taguchi method is proposed by Pei-Wei Tsai, Jeng-Shyang Pan, Shyi-Ming Chen and Bin-Yih Liao in 2012 . EPCSO (11) is proposed to alleviate the limitations of original CSO and Parallel CSO. The EPCSO technique inhibits the two-level orthogonal array from the Taguchi process. In orthogonal array, each column indicates a value of considered factor , which can be evaluated independently. Two level orthogonal array can be represented as below

$$L_n(2^{n-1})$$

Where, $n = 2^k$ and 'k' is a positive integer.

A novel chaotic improved Cat Swarm optimization (12) is developed by Yang shi-da, Yi Ya-lin and Shan Zhi-yong in 2013. The authors have incorporated several chaotic maps into the seeking mode process of original CSO, to improve the global search capability. Yang demonstrated the superiority by comparison with the standard benchmark functions.

V. APPLICATIONS OF CSO

Cat Swarm Optimization has been applied in technology, business, science, space research and social sciences. Researchers and scientists have applied the concepts of CSO to various real-time applications. There are many significant areas in which the algorithm is not been explored, for example; Medical Image Processing, Plant Monitoring, robotics etc.

Figure 3: Applications of Cat Swarm Optimization

- Budi Santosa and Mirsa Kencana Ningrum developed CSO clustering algorithm in 2009 and tested on four data sets (13). The authors have modified the CSO formula and compared with PSO and K-Means Clustering. The accuracy level of the proposed algorithm is deduced by
    - different number of iterations by clustering error
    - cpu time and clustering error of non-modified and modified CSO clustering

  Each Method is iterated for 100 runs on every dataset by the authors.

  The main inference of the method is, though it is accurate, it takes longer time to do the computation. Researchers can concentrate on mechanisms to develop a hybrid method for clustering real data from the real problem.
- Yongguo Liu, Xindong Wu and Yidong Shen (14) developed K-means improvement and Simulated Annealing selection based cat swarm optimization clustering (KSACSOC) in 2012. Experimental results on two artificial and six real life data sets were chosen by the authors to illustrate the superiority of the proposed algorithm.

The comparison algorithms chosen are k-means algorithm, a simulated annealing clustering method, and a particle swarm optimization clustering method. The Experimental data sets chosen are

- Data-52 data set, Data-62 data set,
- Crude oil data set, Fisher' s iris data set,
- Wine data set, Ripley's glass data set,
- Wisconsin breast cancer,
- Vowel data set

The authors had concluded that KSACSOC algorithm had the best results for experimental data sets under the criterion of minimum sum of squares clustering and provided higher success rates than the k-means algorithm, the SAKMC algorithm, and the CPSO algorithm.

VI.CONCLUSION

The research fraternity had utilized, modified, enhanced the original CSO algorithm for solving many real time problems. Few applications and titles in the year 2019 are listed to justify the efficacy and the thrust for CSO even after a decade of its inception.

In spite of multitude of publications in CSO till date, only 259 articles are well written in CSO as per the Google Scholar Reports. Very few modifications of original algorithm have been successful. Thus, the goal is to improve the already existing solutions, refine them, and define them as per the real time applications.

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