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A Survey on Cat Swarm Optimization Algorithm

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Authors' contributions

This work was carried out in collaboration among all authors. Author RRI, SMA and BMSO designed the study, collected the previous works done and wrote the first draft of the manuscript. Author RRS and RBM managed the analyses of the study and the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

Swarm based optimization algorithms are a collection of intelligent techniques in the field of Artificial Intelligence (AI) were developed for simulating the intelligent behavior of animals. Over the years ago, problems complexity increased in a means that it is very difficult for basic mathematical approaches to obtain an optimum solution in an optimal time, this leads the researchers to develop various algorithms base on the natural behaviors of living beings for solving problems. This paper present a review for Cat Swarm Optimization (CSO), which is a powerful metaheuristic swarm-based optimization algorithm inspired by behaviors of cats in the Nature for solving optimization problems. Since its first appearances in 2006, CSO has been improved and applied in different fields by many researchers. In this review, we majorly focus on the original CSO algorithm and some improved branches of CSO family algorithms. Some examples of utilizing CSO to solve problems in engineering are also reviewed.

Keywords: Swarm intelligence; cat swarm optimization; CSO; optimization.

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1. INTRODUCTION

Generally, Optimization refers to the process of finding out the best obtainable solution to a given problem. Optimization Algorithms figures out to be methods of discovering optimized value of a function (objective/fitness function) [1,2]. This process of optimization is generally performed under some system imposed binding conditions known as constraints. Optimization problem can have single objective or multiple objectives. And it's possible to have many maxima or minima in a search space, indeed all of them are not the best solutions [3]. Finding out any of these local optima may disguise the search method of successfully optimizing the problem (Fig. 1). Global optimization refers to finding out the global optimum avoiding local optima.

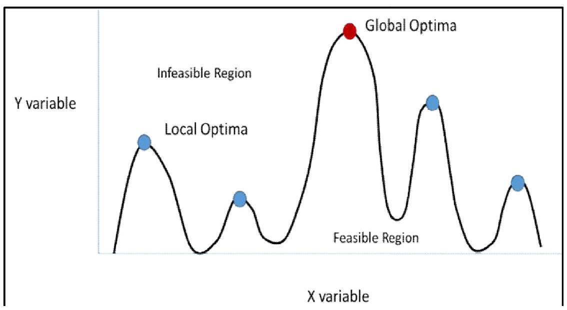

Fig. 1. Search space local and global optima [4]

One key issue of this process is the immensity of the search space for many real-life problems, in which it is not feasible for all solutions to be checked in a reasonable time.

In Computer Science and Engineering fields many algorithms has been designed for solving optimization problems [1]. Typically Swarm Intelligent algorithms and generally Artificial Intelligent algorithms played important rule in solving these optimization problems, such as solving Travelling Salesman Problem (TSP) which belongs to NP-hard problem by Almufti in [1] by using various swarm intelligent algorithms.

This paper gives an overview for a well known swarm intelligent algorithm that inspired the natural behavior of cat for solving optimization problems it called Cat Swarm Optimizations (CSO) [5].

2. SWARM INTELLIGENT

Swarm Intelligence (SI) algorithms are computational intelligence techniques studies the collective behavior in decentralized systems, Such systems are made up of a population of simple individual's agents interacting locally with each other and with the environment around themselves [1]. During the past years, various successful Swarm Intelligence appears that inspired by different behaviors of living beings in the nature, such as Ant Colony Optimization (ACO) that inspired by the behavior of Ant in searching for food [2,3,6], Particle Swarm Optimization (PSO) algorithm concept roots from the social behavior of organisms such as fishing schooling bird flocking [7,8], Bat Colony Optimization (BA) which inspired the bio-inspired metaheuristic on the bio-sonar or echolocation characteristics of bats [9,10,11], Artificial Bee Colony (ABC) that is inspired from the intelligent, interactive and foraging behavior of real honey bees in searching for food sources “nectar”, and announcing other bees in the nest about the information of food source [1,12,13], Elephant Herding Optimization (EHO) inspired by herding behaviors of elephants in their clan [14,15,16]. According to P. Agarwal and S. Mehta in [17], S. Almufti in [18] and J. Rajpurohit et al. in [19], there are more than 200 algorithms that are inspired from the natural phenomenon and characteristics of living beings, that have been used for solving various problems in different fields.

This paper, reviews the Cat Swarm Optimization (CSO) which is swarm intelligence algorithms for finding the best global solution [5]. Sometimes the pure CSO takes a long time to converge and cannot achieve the accurate solution. For solving this problem and improving the convergence accuracy level, various modifications has been made in the original CSO. This paper presents an overview of the original CSO and its modifications.

3. CAT SWARM OPTIMIZATION

Cat Swarm Optimization is swarm intelligence algorithms introduced by Chu, Tsai, and Pan in the year 2006 for solving optimizations problems [5,18,20] based on the behavior of cats.

The original CSO algorithm was designed for solving a continuous and single-objective problems [5]. In the nature, Cats are lazy animal and spend most of the time on rest. but, during the resting, Cats awareness is very high and they are conscious of what happens in around, and are continuously intelligently observing around them, and whenever they find target they start quickly moving towards that target. CSO algorithm has been designed based on combining these two characteristics of cats [20].

Cat Swarm Optimization algorithm consists of two modes: seeking and tracing modes [5]. Each cat represents an agent has three main variables:

- Position: is a M-dimensions in the search space, and each dimension has its own velocity.
- Fitness: is a value shows how well the solution set (cat) is
- Flag: is to classify the cats into either seeking or tracing mode

CSO should first specify how many cats should be engaged in the iteration and run them through the algorithm. To combine the two modes into the algorithm, a mixture ratio (MR) is defined. This parameter is chosen from the interval of [0, 1] and it determines what percentage of cats are in seeking mode and what percentage are in tracing mode. The best cat in each iteration is saved into memory until the stop criteria is achieved, and the one at the final iteration will represent the final solution [21].

a. Seeking Mode:

For modeling the behavior of cats in resting time and being-alert, CSO corresponds the seeking mode. This mode is a time for thinking and deciding about next move. This mode has four main parameters which are mentioned as follow: seeking memory pool (SMP), seeking range of the selected dimension (SRD), counts of dimension to change (CDC) and self-position consideration (SPC) [5,22], as shown in Fig. 2.

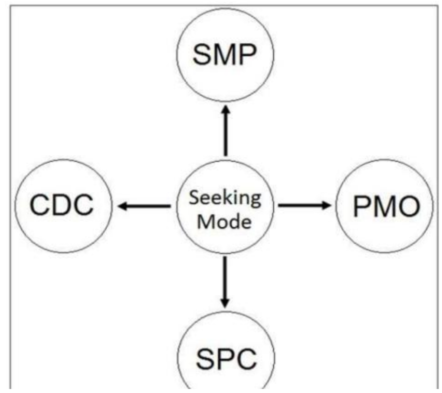

Fig. 2. CSO seeking mode parameters [23]

- SMP is used to define the size of seeking memory for each cat. SMP indicates the points explored by the cat. This parameter can be different for different cats.
- SRD declares the mutation ratio for the selected dimensions.
- CDC indicates how many dimensions will be varied. For example, if the search space has 5 dimensions and CDC is set to 0.2, then for each cat, four random dimensions out of the five need to be modified and the other one stays the same.
- SPC is a Boolean flag, which decides whether current position of cat will be one of the candidates to move to or not.

The process of seeking mode is describes as follow:

Step 1. Make j copies of the current location of cat k, where j = SMP. If the value of SPC is true, let j = (SMP-1), then retain the present position as one of the candidates by Eq. (1).

$$j = \begin{cases} SMP, & SPC = \text{"}true\text{"} \\ SMP - 1, & SPC = \text{"}false\text{"} \end{cases} \tag{1}$$

Step 2. For each copy, according to CDC, randomly plus or minus SRD percent the present values and replace the old ones by Eq.(2).

$$Xjd_{new} = (1 + rand * SRD)Xjd_{old} \tag{2}$$

where Xjd_{old} is the current location; Xjd_{new} is the next location; j denotes the number of cats and d represents the dimensions; and $rand$ is a random value $rand \in [0,1]$.

Step 3. Calculate the fitness values (FS) of all candidate points.

Step 4. If all FS are not exactly equal, calculate the selecting probability of each candidate point by Eq. (3), otherwise set all the selecting probability of each candidate point be 1.

$$p_i = \begin{cases} 1, & when \;\; fS_{max} = fS_{min} \\ \frac{|fS_i - fS_b|}{fS_{max} - fS_{min}}, & when\; 0 < i < j, otherwise \end{cases} \tag{3}$$

Step 5. Randomly pick the point to move to from the candidate points, and replace the position of cat k.

b. Tracing Mode

This mode copies the tracing behavior of cats. For the first iteration, random velocity values are given to all dimensions of a cat's position. However, for later steps, the next move of each cat is determined based on the velocity of the cat and the best position found by members of cat swarm [22,24]. This mode can be summarized in 3 steps as follows:

Step 1. Update velocities ($v_{k,d}$) for all dimensions by Eq. (4).

$$v_{k,d} = v_{k,d} + r_1 c_1 * (x_{best,d} - x_{k,d}) \tag{4}$$

Where, $x_{best,d}$ represents the location of the cat with the best fitness value; $v_{k,d}$ represents the velocities, $x_{k,d}$ is the current location of cat k in dth dimension. c_1 represents a constant value $\in [0,2]$ and r_1 is a uniform random value $\in [0,1]$.

Step 2. Check if the velocities are within the bounds of velocity. In case the new velocity falls out of the range, set it to the limits.

Step 3. Update the position of cat k according to Eq.(5).

$$x_{k,d} = x_{k,d} + v_{k,d} \tag{5}$$

For combining Seeking and Tracing modes the algorithm defines a mixture ratio (MR) which indicates the rate of mixing of seeking mode and tracing mode, as shown in Fig. 3 [24]. MR parameter decides how many cats will be moved into seeking mode process by Eq.(6).

$$C_{seeking} = C_{num} + MR \tag{6}$$

Where $C_{seeking}$ is the number of cuts in the seeking mode, $C_{num}$is the total number of cats, and MR parameter $\in [0,1]$.

For example, if the population size is 25 and the MR parameter is equal to 0.6, there should be 25×0.6=15 cats move to seeking mode and 10 remaining cats move to tracing mode in this iteration [24]. We summarized the CSO algorithm below flowchart Fig. 4.

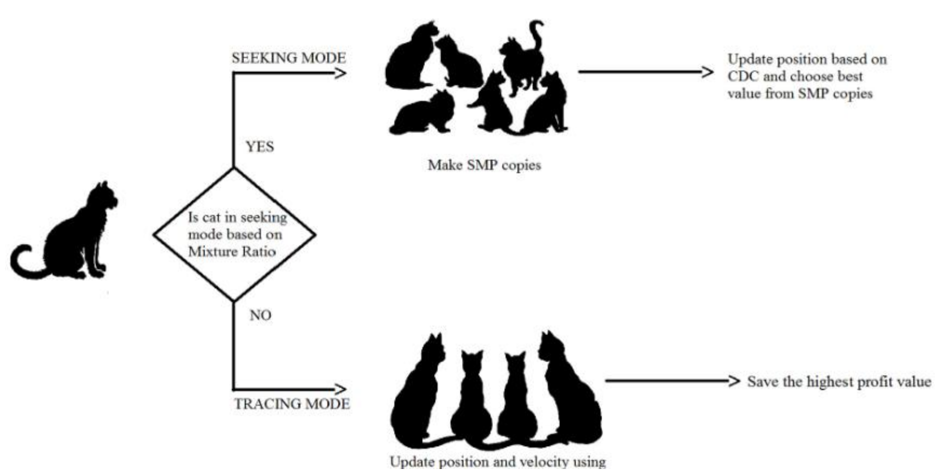

Fig. 3. CSO cats mode [25]

Fig. 3, shows that CSO checks the cat mode whether its Seeking or Tracking. In the Seeking mode the position of cat are updated as shown in Fig. 2, whereas when a cat is tracking mode the algorithm saves the highest fitness value.

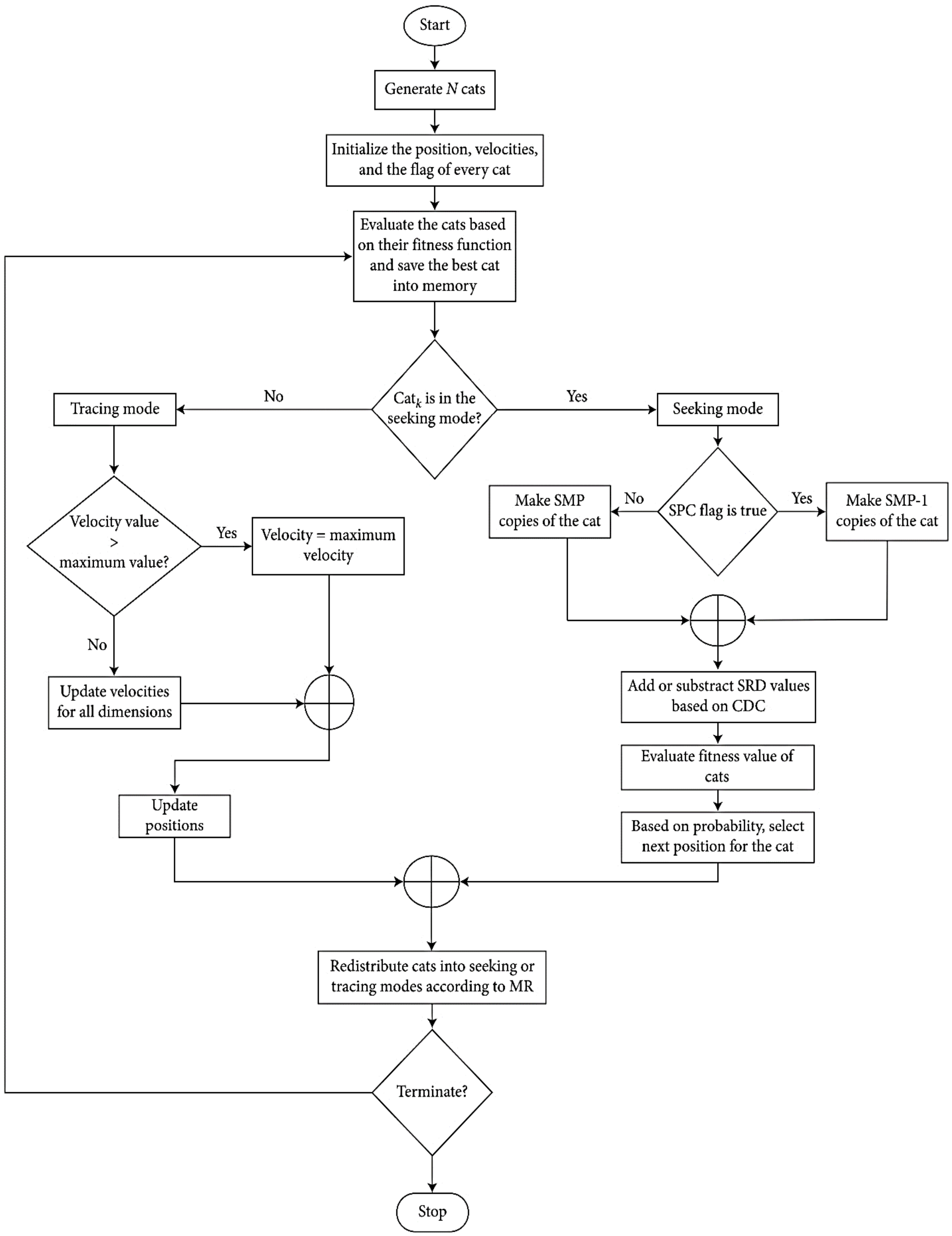

Fig. 4. CSO flowchart [5]

4. MODIFICATIONS OF CSO

After the appearance of Cat Swarm Optimization (CSO) algorithm in 2006 [5,18], many modifications has been applied to the original CSO to improve the performances of the proposed algorithm. In this section, some of the modifications and improvements of the CSO algorithm are listed and arranged according to the development year, as shown in Table 1.

Table 1. CSO algorithm are listed and arranged according to the development year

ID	ABBR.	Name	Year	Authors	Ref.
1.	PCSO	Parallel Cat Swarm Optimization	2008	Tsai et al.	[26]
2.	CSO Clustering	CSO Clustering	2009	Santosa et al.	[27]
3.	AICSO	Average-Inertia Weighted CSO	2011	Orouskhani et al.	[24]
4.	hybrid PCSOABC	hybrid system by combining PCSO with ABC algorithms	2011	Tsai et al.	[28]
5.	CSO + SVM	hybrid system based on SVM and CSO	2011	Wang et al.	[29]
6.	CSO/PSO + ANN	CSO and PSO algorithms to train ANN	2011	Chittineni et al.	[30]
7.	EPCSO	Enhanced Parallel Cat Swarm Optimization	2012	Tsai et al.	[31]
8.	MOCSO	Multiobjective Cat Swarm Optimization	2012	Pradhan et al.	[32]
9.	CSO + ANN + OBD	ANN with CSO algorithm and optimal brain damage (OBD) approach	2012	Yusiong	[23]
10.	BCSO	Discrete Binary Cat Swarm Optimization Algorithm	2013	Sharafi et al.	[33]
11.	ADCSO	Adaptive Dynamic Cat Swarm Optimization	2013	Orouskhani et al.	[34]
12.	ADCSO + GD + ANFIS	combined ADCSO algorithm with gradient descent (GD) algorithm	2013	Orouskhani et al	[35]
13.	Enhanced HCSO	Enhanced Hybrid Cat Swarm Optimization	2014	Hadi et al.	[36]
14.	BCSO + SVM	classification model based on BCSO and SVM	2014	Mohamadeen et al	[37]
15.	ICSO	Improvement Structure of Cat Swarm Optimization	2015	Hadi et al.	[38]
16.	ICSO	Improved Cat Swarm Optimization	2015	Kanwar et al.	[39]
17.	CSO-GA-PSOSVM	CSO with particle swarm intelligence (PSO), genetic algorithm (GA), and support vector machine (SVM)	2015	Vivek et al.	[40]
18.	MCSO	Modified Cat Swarm Optimization	2015	Lin et al.	[41]
19.	CSO + WNN	hybrid system by combining wavelet neural network (WNN) and CSO algorithm	2015	Nanda	[42]
20.	CCSO + ANN	CSO and ANN that can handle randomness, fuzziness, and accumulative time effect in time series concurrently	2015	Wang et al.	[43]
21.	NMCSO	Normal Mutation Strategy-Based Cat Swarm Optimization	2016	Mohapatra et al.	[44]

ID	ABBR.	Name	Year	Authors	Ref.
22.	CS-FLANN	combined the CSO algorithm with functional link artificial neural network (FLANN)	2016	Kumar et al.	[45]
23.	OL-ICSO	Opposition-Based Learning-Improved CSO	2017	Kumar et al.	[46]
24.	CQCSO	Chaos Quantum-Behaved Cat Swarm Optimization	2017	Nie et al.	[47]
25.	Hybrid CSO-Based Algorithm	Hybrid CSO-Based Algorithm	2017	Skoullis et al.	[48]
26.	Hybrid CSO-GA-SA	hybrid system by combining CSO, GA, and SA	2017	Sarswat et al.	[49]
27.	CSO-CS	Hybrid Cat Swarm Optimization-Crow Search	2017	Pratiwi et al.	[50]
28.	CCSO	Compact Cat Swarm Optimization	2018	Zhao	[51]
29.	BBCSO	Boolean Binary Cat Swarm Optimization	2018	Siqueira et al.	[4]

Those modifications were required so that CSO can be applied in various fields and for solving different problems in the real life, because each problem represent a different situations and it needs a specific steps to be taken by researches to solve them by CSO algorithm.

Since its introduction, CSO and its modified algorithms has potential applied in a wide to solve various problems in several fields. Some problems that have been solved by researchers by using different versions of CSO [52-54] are listed bellow,

- Electrical payment system in order to minimize electricity cost for customers
- Economic load dispatch (ELD) of wind and thermal generator
- Unit commitment (UC)
- To classify the feasibility of small loans in banking systems
- UPFC to increase the stability of the system
- To optimize the network structures for pinning control
- Reactive power dispatch problem to minimize active power loss
- To regulate the position and control parameters of SVC and TCSC to improve available transfer capability (ATC)
- To find the overlapping community structures.
- Clustering mechanism in web services.
- To solve tsp problem
- On workflow scheduling in cloud systems
- Building a classification model based on BCSO and SVM to classify the transformers according to their reliability status
- To optimize the network structure and learning parameters of an ANN model named CPNN-CSO, which is used to predict household electric power consumption
- Distributed generation units on distribution networks
- Signal processing.
- System management and combinatorial optimization
- Wireless and WSN
- Modern benchmark functions
- To achieve global maximum power point (GMPP) tracking
- To optimize the location of phasor measurement units and reduce the required number of PMUS

and many other applications in various fields.

5. CONCLUSION

This paper presents a review on one of swarm inspired algorithms known as Cat swarm optimization (CSO) to deal with global optimizations missions, the paper firstly addressed this overviewed the original CSO algorithm and then it presented some of its modifications, finally some of its applications has been listed. by idealizing the cat behavior in nature through “Tracing & Seeking” mood. CSO has no complicated operators, which makes its implementation easy and fast. At the early steps of CSO method it only depend on three major variables (Position, Fitness, and flag), where

Position represents a M-dimensions in the search space, and each dimension has its own velocity. Fitness is a value shows how well the solution set (cat), and flag is uses to classify the cats into either seeking or tracing mode.

Sence the first appearance of CSO, many times it has been modified by researches as shown in Table 1, and it has been applied to solve various problem in the real life such as (Wireless Sensor Network Localization Problem, QoS aware web service composition, Benchmark problem, and Traveling Salesman Problem).

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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