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Cheetah Based Optimization Algorithm: A Novel Swarm Intelligence Paradigm

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Abstract. All the new gadgets, systems and advances in technology are bringing the actual engineers problems with increasing complexity. To solve those problems, the optimization algorithms are popping up to support and even improve the actual scenario. Several stochastic optimization paradigms called metaheuristics are being proposed each year and the inspiration comes from animals, plants, experiments, chemical processes or simply math. In this paper, a cheetah based optimization algorithm (CBA) is proposed, capturing the social behavior from those animals. The proposed CBA is validated against seven known optimizers using three different benchmark problems. Finally, some considerations about research issues and directions in the CBA design are given.

1 Introduction

Nature seems a quite good laboratory where processes are occurring trough thousands of years recurrently, and are improved on by each of the natural interactions. Inspired by plants, like the flower pollination algorithm [1], or by animal behavior like elephant herding behaviour [2], mimicking the nature sounds a promising strategy. More details about bio-inspired optimization metaheuristics can be found in [3].

Looking for this nature knowledge library, the behavior of the African Cheetah is copied to an optimization algorithm. Those animals are being studied since 1940’s and they capture the attention of many biology researchers [3-5]. Cheetahs are living in the African planes. They are the fastest terrestrial animals, reaching more than 100 km/h in a hunting sprint. They have a hierarchical social arrangement, driven mainly by the individual age, gender and group. In this paper, a cheetah based optimization algorithm (CBA) to single-objective optimization problems is proposed that tries to capture the social behavior from those animals. The bio-inspired CBA presents a variable population structure, where all constructive parameters are driven by the biologic available data. Six benchmark optimization problems were adopted to test the

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effectiveness of the proposed CBA. In this context, simulation results obtained through CBA and those of the state-of-art optimizers in the literature are compared.

The remainder of this paper is organized as follows. The CBA, its rules and considerations are explained in Section 2. After, Section 3 presents the setup for the experiments and the results analysis to three benchmark optimization problems. Finally, a conclusion is outlined in Section 4.

2 The Cheetah Algorithm (CBA)

The CBA implementation is based on natural observations from Durant et al. [4]. Those animals are the fastest terrestrial ones, but this is not the only characteristic which calls the attention from researchers since 1940's. They are arranged in a social environment where age and gender rules most of the animal behavior.

Durant et al. [4] show the examination of environmental and social factors affecting reproductive success across a 20-year data set of individually known cheetahs on the Serengeti Plains of Tanzania. Serengeti is an African plane land about 25,000km^2. According to [5], Serengeti plane is the Earth place that holds the greatest amount of mammals. Among those mammals, lions, *Panthera leo* and cheetahs *Acinonyx jubatus* are the largest felines. Another unique fact from this plane is that every year around two million animals move along searching for food due to the raining season.

At Serengeti, cheetah females control a range area about 833km^2 (3% of the total land) and males use to hunt in an area of 37km^2 (0.1% of the total land). Males can also take a behavior of walking randomly on areas about 700km^2 (2.5% of the total land). Females stand for 60% to 70% of the population.

There are some interesting behaviors that could be captured from the cheetah nature. Adult females live alone or with their cubs. Males can live in groups up to three individuals even in an adult phase. Cubs are aged from 0 to 1 year, adolescents from 1 to 2 years and adults are older than 2 years.

The female mean life is 7.01 with a standard deviation of 12.27 years. Males live in mean 3.60 years with a standard deviation of 1.83. According to [4] the oldest female was recorded having 13.6 years once the oldest male had 7.8.

The cheetah demographic yearly rate is around 1, what means the newborn and death rates are equivalent defining the population as stationary. The yearly rain occurrence rules the food offer and consequently the gazelle population. This population is the main food source for the large felines [4].

Parameter	Value
Serengeti plain area	25,000 km^2
Mean female life expectation	12.27 ± 7.01years
Mean male life expectation	3.60 ± 1.83 years

Table 1: List of parameters related to the cheetahs behavior.

The main goal on the algorithm implementation was to capture with high fidelity the animal behavior. In order to achieve that, the main environmental parameters were set in the beginning of the code. Those parameters are: the Serengeti plains area, the mean life according to gender, and the proportional territory by gender. The only free parameter that the user could change is the initial population size, *N*. The list of parameters is shown in Table 1. Other parameters like the gender distribution are adjusted according to the nature. After loading the environmental parameters, the population is initialized randomly using uniform distribution.

Prior to the individual evaluation, the gender is attributed to each population member. This rate is defined according to the nature by a distribution with 0.65 as mean and standard deviation as 0.05 given by

$$nf = 0.65 + (r * 0.05) \;, \tag{1}$$

where *nf* stands for the size of the female group and *r* is a random number generated using uniform distribution in range [0,1]. The remainder of the population is set as male. Once the reproductive characteristic is quite interesting in the first searching round, then all initial population members are set as adults respecting the mean life information. All individuals (cheetah or potential solutions) are evaluated using the problem to be solved and the individual best result and general best result among all individuals are recorded. The evaluation metrics are recorded as well at the end of each searching loop.

Those first steps are ending the initial procedures and then a recurrent searching loop will take place. The searching loop will be ended if the maximum number of functions evaluations is reached or if the target objective is reached. Any loop execution stands for a month-life for the population, meaning the CBA shall run 12 times in order to reach a year in time-lapse. The first action on the searching loop is to copy the actual population into an old population matrix in order to evaluate if the new selection is better or not. The first population movement will occur on the female portion. The movement is ruled by the following equation:

$$x_f(k+1) = x_f(k) + \alpha.[x_{best}(k) - \mathrm{x}_{fbestr}(k)], \tag{2}$$

where x_f is the female population members, x_{best} is the best global answer from the algorithm up to moment, x_{fbestr} is a randomly selected best female individual, α is a random number generated with uniform distribution in range [0,1]. This movement aims to reproduce the learning life capacity that each female could get from other females even living in their own home range.

There is a natural repulsion between females and each one will take care of its home range. Weaker females will be driven away by the stronger ones. In order to simulate this behavior, females are ranked according to the fitness, better fitness means stronger females. The Euclidean distance calculation among the females will be performed and if a female is detected in one female home range, then the weaker one position will be changed according to:

$$x_{fi}(k) = x_{fi}(k) + \beta.fpa, \tag{3}$$

where x_{fi} is the weaker female member, *fpa* is the standard territory area and β is a random number generated with uniform distribution in range [-1, 1].

The next movement group is the males one. The distance among all population members is calculated before moving them. Males movement is selected randomly between two possible behavior rules:

i) If there are free females, the male will move towards the closest free one, according to the equation:

$$x_{mi}(k) = x_{mi}(k) + \alpha 1.[x_{cfi}(k) - x_{mi}(k)] \tag{4}$$

where x_{mi} is the male population member, x_{cfi} is the closest females and $\alpha 1$ is a random number generated with uniform distribution in range [0, 1].

ii) Male will move freely, likes an errant:

$$x_{mi}(k) = x_{mi}(k) + \alpha 2.(b_x) \tag{5}$$

where x_{mi} is the male population members, b_x is a boundary value randomly selected for each problem dimension and $\alpha 2$ is a random number generated with uniform

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distribution in range [0,1]. If there are no free females to mate, then all males will select the errant behavior. In the first movement rule given by eq. (4), a newborn will be generated after the males movement. The number of new individuals is choosen randomly from 2 up to 5, according to the biology data. Each new member is assembled by the linear combination from the best mother's position ever and the best father's position ever. Then the newborn problems dimension, are permuted, forming new combinations for the newborns. All new individuals have a group number assigned that is also assigned to their mother.

The next group to be moved is the adolescents. This group is formed by individuals of the two available genders, males and females, which are between 13 and 24 months old and move in groups. In the mathematical implementation, the population members will move ruled by the following equation:

$$x_{ai}(k) = x_{ai}(k) + \alpha 3. [x_{best}(k) - x_{bestgr}(k)] \tag{6}$$

where x_{ai} is the adolescent population members, x_{best} is the best global answer from the algorithm up to moment, x_{bestgr} is the best group member position so far and $\alpha 3$ is a random number generated with uniform distribution in range [0,1]. The rule is the same as used to change the positions for the females group, however the reference is the adolescent group and there is no spacing once no home range have to be secured in this case.

Finally, the last groups to be moved are the cubs. They are the newborns up to the first year. Their movement will be ruled by the mothers movement simulating that they are learning from their mother. The movement rule is given by

$$x_{ci}(k) = x_{ci}(k) + \alpha 4. [x_{fm}(k) - x_{ci}(k)] \tag{7}$$

where x_{ci} stands for the cub population members, x_{fm} is the cubs mother's position and $\alpha 4$ is a random number generated with uniform distribution in range [0,1].

Members are then evaluated and ranked. Once males present a errant natural behavior the position is always updated with the current fitness, even if it is worse than the actual one. Other population members like cubs, adolescents and females have their position changed only if the actual fitness is better than the old one. Once the demographic yearly rate is around 1, a death algorithm will take place to simulate the cheetahs killed by lions, hyenas and starving. This algorithm will randomly keep the population near to the initial members number regulating the proportional rate between females and males according to the biological observations [4].

Finally, the best position ever is checked against the new population and if there is a new best ever it will replace the actual one. The best individual position for each member will be stored for mating purpose and the search cycle will start again. The flowchart of the CBA is showed in Fig. 1.

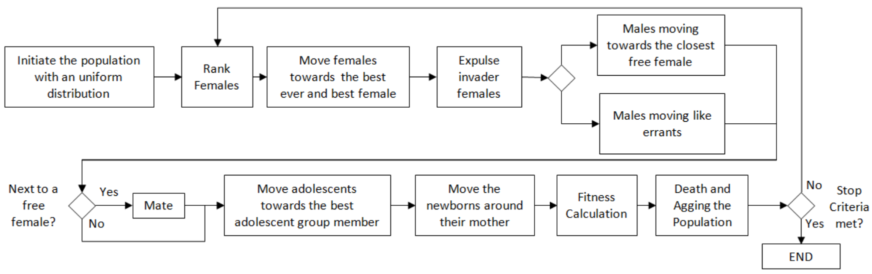

Fig. 1: Flowchart of the CBA.

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3 Benchmark Functions and Results Analysis

The test functions selected for the algorithms comparison were obtained of the IEEE CEC2014 competition [7]. The searching field was bounded in a continuous range from -100 to +100. In order to assure some statistical analysis, all algorithms run each problem 25 times. The maximum number of function evaluations allowed for all algorithms was set to 10^5. The maximum error against the objective value was set to 10^{-8}.

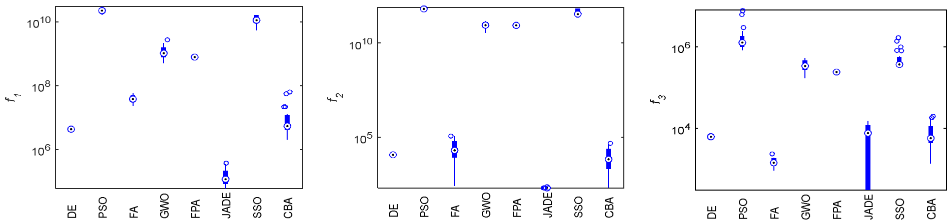
The results for the three unimodal and the three multimodal benchmarks problems of the IEEE CEC2014 competition [7] for dimension *D* equal to 100 are summarized in Figure 2. In those results, the CBA is compared to algorithms that are already in the literature. There were chosen some nature inspired, animal and flowers, and some differential evolution strategies. The benchmark algorithms are: differential evolution (DE) [8], JADE [9], particle swarm (PSO) [10], social spider optimizer (SSO) [11], grey wolf optimizer (GWO) [12], artificial fireworks (FA) [13], and flower pollination (FPA)[1].

The first CEC2014 problem result is shown on Figure 2(a). The function tested is called rotated high conditioned elliptic function. One can see that CBA median value was only worse than DE and JADE. Similar inspiration algorithms like the GWO and SSO presented worse values than CBA. Percentile dispersion presented by the CBA are similar to the one presented by JADE. The second tested function was the rotated bent cigar function. CBA presented the second best median result being overtaken only by JADE. DE and FA showed near performance and the other nature inspired algorithms achieved worse performances. CBA percentile spread was similar to the one presented by FA. The latest unimodal tested problem is called rotated discus function and its results can be seen in Figure 2(c). CBA showed the third best median performance being overtaken by FA and DE. No nature inspired algorithm besides FA could achieve results like CBA for the third test case.

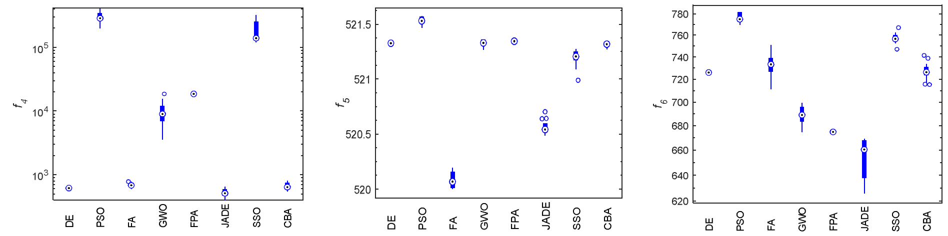
The first multimodal problem results are presented in Figure 2(d). CBA showed the third best median performance being overtaken by JADE and DE. FA median performance was near to CBA, but not better. No nature inspired algorithm could be better than CBA for the fourth test case. The fifth tested function is called shifted and rotated Ackley's function and its results are shown in Figure 2(e). CBA achieved the fourth best median performance. FA, JADE and SSO have presented better median results. Finally, the latest test case was on the shifted and rotated Weierstrass function. Results are presented on Figure 2(f). CBA presented the fourth best median performance tied with DE. The best median results could be achieved by JADE, FPA and GWO.

4 Conclusion and future research

CBA is a paradigm that mimics the social behavior and hierarchy from the African Cheetahs. It has no control parameters to be tune once all needed are based on nature observations. Comparing the test result from already known algorithms, bio-inspired and not, CBA presented an average global result. CBA shows to be a promising bio-inspired optimization method.



a) rotated high conditioned elliptic function b) rotated bent cigar function c) rotated discus function



d) Shifted and rotated Rosenbrock's function e) Shifted and rotated Ackley's function f) Shifted and rotated Weierstrass function

Fig. 2: Optimization results to six IEEE CEC2014 benchmark functions (D = 100).

References

[1] X. S. Yang, Flower pollination algorithm for global optimization. Unconventional Computation and Natural Computation. Lecture Notes in Computer Science, vol. 7445, pp. 240-249, 2012.

[2] G. G. Wang, X. Gao and L. S. Coelho, A new metaheuristic optimisation algorithm motivated by elephant herding behaviour. *International Journal of Bio-Inspired Computation*, 8(6): 394-409, 2016.

[3] S. Salcedo-Sanz, Modern meta-heuristics based on nonlinear physics processes: A review of models and design procedures, *Physics Reports*, 655: 1-70, 2016.

[4] S. Durant, K. Marcella and T. Caro, Factors affecting life and death in Serengeti cheetahs: Environment, age, and sociality, *Behavioral Ecology*, 15(1): 11-22, 2004.

[5] A. Sinclair, *Serengeti Story: Life and Science in the World's Greatest Wildlife Region*. Oxford University Press (OUP), USA, 2012.

[6] B. Kaltenborn, J. Nyahongo, J. R. Kidegesho and H. Haaland, Serengeti National Park and its neighbours – Do they interact?, *Journal of Nature Conservation*, 16: 96-98, 2008.

[7] J. J. Liang, B. Y. Qu and P. N. Suganthan, Problem definitions and evaluation criteria for the CEC 2014 special session and competition on single objective real-parameter numerical optimization. *Technical Report 201311*, 2013.

[8] R. Storn and K. Price, Differential evolution - A simple and efficient heuristic for global optimization over continuous spaces, *Journal of Global Optimization*, 11: 341-359, 1997.

[9] J. Zhang and C. Sanderson, JADE: Adaptive differential evolution with optional external archive. *IEEE Transactions on Evolutionary Computation*, 13(5): 945-958, 2009.

[10] J. Kennedy and R. Eberhart, Particle swarm optimization. In *Proceedings of the IEEE International Conference on Neural Networks*, Perth, Australia, vol. 4, pages 1942-1948, 1995.

[11] E. Cuevas, M. Cienfuegos, D. Zaldívar and M. Pérez-Cisneros, A swarm optimization algorithm inspired in the behavior of the social-spider, *Expert Systems with Appl.*, 40(16): 6374-6384, 2013.

[12] S. Mirjalili, M. S. Mirjalili and A. Lewis, Grey wolf optimizer, *Advances in Engineering Software*, 69: 46-61, 2014.

[13] Y. Tan and Z. Yuanchun, Fireworks algorithm for optimization. In *Proceedings of the 1st International Conference in Swarm Intelligence* (ICSI), Beijing, China, Lecture notes in Computer Science 6145, pages 355-364, Springer, 2010.