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Meerkats-inspired Algorithm for Global Optimization Problems

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Abstract. Bio-inspired computing has been a relevant topic in scientific, computing and engineering fields in recent years. Most bio-inspired metaheuristics model a specific phenomenon or mechanism based on which they tackle optimization problems. This paper introduced the meerkats-inspired algorithm (MEA) a novel population-based swarm intelligence algorithm for global optimization in the continuous domain. The performance of MEA is showcased on six classical constrained engineering problems from literature. Numerical results and comparisons with other state of the art stochastic algorithms are also provided. Results analysis reveal that the MEA produced consistent results when compared with other optimizers.

1 Introduction

During the past decade, solving complex optimization problems with metaheuristic algorithms has received considerable attention among practitioners and researchers. Hence, many metaheuristic algorithms [1-3] have been developed over the last years.

The No Free Lunch theorem [4] states that no single algorithm can perform well on every optimization problem, encouraging the development of new metaheuristics. These techniques are generally inspired from various everyday phenomena and are predominantly nature inspired.

The proposed meerkat-inspired algorithm (MEA) is based on the meerkat behavior analysis related in [5,6]. The main idea is to use the animal behavior not only for the optimization strategy, but also for the parameter selection. This means only one parameter is selectable by user for MEA, and it stands for the initial population size. These base papers [5,6] show the examination of meerkats groups, their relationships and social organization across a 7-year dataset. The biological research was conducted in the Kalahari Gemsbok National Park, republic of South Africa. This national park has 38,000 km2, interfacing with other wildlife park in Botswana.

In this paper, six benchmarks extracted from the IEEE CEC2014 (The Institute of Electrical and Electronics Engineers, Congress on Evolutionary Computation 2014)

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competition [7] were adopted in order to check the performance of the proposed MEA when compared with state-of-art optimizers in the recent literature.

The remainder of this paper is organized as follows. The fundamental and the flowchart of MEA 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 and the future research is outlined in Section 4.

2 Fundamentals of the Meerkat-inspired Algorithm (MEA)

A survey on 1999, counted 33 different groups of meerkats leaving mainly on river beds [5]. Ten of those groups lived in about 100 km2. Those groups did not travel more than 500 meters towards the dunes which are in the river neighborhood. Each group occupied around 5 km2. Groups composition was, in average, equalitarian between females and males (1.89 males, 1.90 females and 1.03 juveniles). In 1994, groups have from 3 up to 14 individuals.

Litters are coming up in all months of the year except in July, with an average of 0.14±0.1 litter per month. Rainfall is one of the most important triggers to reproduction that could take from 1.8 up to 2.7 litter per group per year. Around 80% of pregnancies are from the dominant females and they can produce up to four litter per year. Litter size is ranging from 1 to 8 individuals and in average 4.1±1.5.

Dominant members were older and heavier than other group members. Females begin to breed between 24 and 36 months. There is no significant difference on mortality between sexes or ages. The annual mortality rate of adults was 0.68, however the rainfall rate can impact breeding and so a decline in rainfall can bring the groups in half size in one year period. These mentioned features were inspiration to develop the proposed MEA.

In the MEA, the mathematical representation of a meerkat groups considers only one control (constructive) parameter, N, that stands for the initial population size, which must be pair once the initial groups shall be formed by a male and a female individuals. The mathematical implementation follows the idea that each interaction corresponds to a chronological month for a given population, called here month-life.

Individual positions are initialized randomly and the nearest partners are grouped forming a couple. All individuals are then evaluated on the cost function and the best answer and best fitness are recorded. The initialized elements are always considered to be adults once the algorithm takes different strategies for adults and non-adult. All individuals are listed in a matrix where each line stands for an individual position and columns are arranged like the Fig. 1.

Element [1 - *Dim*]	Fitness	Age	Gender	Group	Dominance	Special attribute	Sequence number

Fig. 1: Individual arrangement adopted in the MEA.

The first step on the searching loop is to calculate the group centers taken in consideration the group range. The maximum group range is stated proportionally as it is in biology, $5km^2/100km^2$ which leads each group to have 5% of the total searching field.

Group individuals are then moved according to their sex, breed rate and the group center. The breed rate is initiated in the first loop with maximum number but at the end of each interactive loop the breed rate is calculated according to the groups prosperity which is taken as the fitness progress or analog to the rainfall in nature.

First group to be moved is the adult one. The movement for this group is ruled by:

$$x(k) = x(k\text{-}1) + rr \cdot [x_{r1}(k\text{-}1) - x(k\text{-}1)], \quad (1)$$

where x stands for the individual position, k for the sample time, rr is the running rate and x_{r1} is a random selected adult position from the historical data using uniform distribution in range [0,1]. The new position for each individual will only be assumed if it is better than the actual one.

The second group to be moved is the newborns. Newborns are cared by the nurse individuals or by their mothers. If the mother is alive the movement is given by:

$$x(k) = x(k\text{-}1) + rr \cdot r_3 \cdot [x_{mother} - x(k\text{-}1)] + r, \quad (2)$$

where r_3 is a random number generated using uniform distribution in range [0,1], x_{mother} is the mother's position and r is a noise signal generated using uniform distribution in range [0,1]. The parameter rr is an unitary gain which decreases proportionally to the optimization goal achievement.

Newborns can be moved according to the group center if their mothers dead. This movement is given by:

$$x(k) = x(k\text{-}1) + rr \cdot r_3 \cdot [x_{center} - x(k\text{-}1)] + r, \quad (3)$$

where x_{center} is the group's central position. Newborn's new position is assumed either way if it is better or not in relation to the actual one.

When all individuals have moved, then the mating operation takes place. Mating males are selected according to their size in the groups, which are related to the problem fitness values. Bigger males, which have a better fitness values, have more chance than smaller ones as the domination rule. The number of newborns for each female is randomly chosen between 2 and 6, but this number is multiplied by the rain fall rate.

Newborns are also formed in relation to parents domination. If the male is bigger (better fitness) than the female, the newborn is formed as:

$$x(k) = x_{male} + r \cdot [x_{female} - x_{male}] + r_{-1}, \quad (4)$$

where x_{male} is the male position, x_{female} is the female position, r is a random number generated using uniform distribution in range [0,1] and r_{-1} is noise signal generated using uniform distribution in range [-1,1]. On the contrary, if the female is the dominant one, then the breed is according to:

$$x(k) = x_{female} + r \cdot [x_{male} - x_{female}] + r_{-1}, \quad (5)$$

After, new individuals are evaluated and ranked. MEA works with the annual grow rate as unitary and so the number of newborns in one year period will be taken out from the population. The death part of the algorithm keeps the sharing rate between males and females and also selects the weaker individuals as the less adapted ones. When the population movement, mating and death are over, the group performance is checked. This calculation is made using:

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$$grp_{perf} = 1 - (FS_{newgroup} - FS_{target}) / (FS_{best} - FS_{target}), \quad (6)$$

where grp_{perf} is the actual group performance, $FS_{newgroup}$ is the best actual fitness for the group, FS_{best} is the best actual fitness for the population and FS_{target} is the fitness goal. The running rate, used on the movement equations is taken from the Table 1 values. Table 1 serves to relate the group performance with other two dimensions called performance rate and running rate. They are dynamically accessed by the group performance as a look-up table in order to calculate and adjust the algorithm methods.

Parameter	Value 1	Value 2	Value 3
Group performance	0	0.5	1
Performance rate	0.75	1.7	3.5
Running rate	1	0.5	0.01

Table 1: Group performance, performance rate, and running rate adopted in the MEA.

The searching loop will be running up to the maximum number of function evaluation to be reached or if the optimization error is less than the minimum acceptable error. Figure 1 shows the flowchart of the proposed MEA.

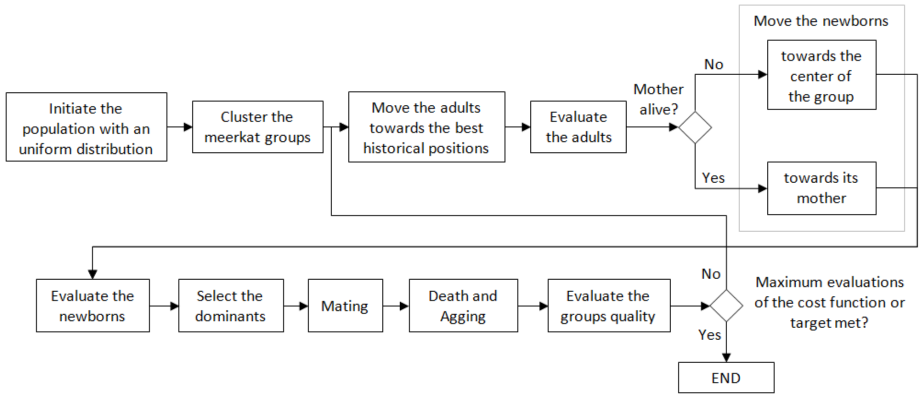


Fig. 1: Flowchart of the proposed MEA.

3 Benchmark Functions and Compared Optimizers

In the IEEE CEC2014 benchmarks competition [7], the searching field was bounded in a continuous range [-100, 100]. In order to assure some statistical analysis, all optimization algorithms run all problems 25 times with different random numbers initial seed, but it is the same among all algorithms. The maximum number of function evaluations allowed for all optimizers was set to 10^5 and tolerance (maximum error) against the objective function value was set to 10^{-8}. This means all optimizers will stop searching when the objective function error is smaller than 10^{-8} or the number of function evaluations is greater than 10^5. The optimization metaheuristics adopted to MBA comparison including: differential evolution (DE) [8], particle swarm optimization (PSO) [9], fireworks algorithm (FA) [10], grey wolf optimizer (GWO) [11], flower pollination (FPA) [12], JADE [13] and social spider optimizer (SSO) [14].

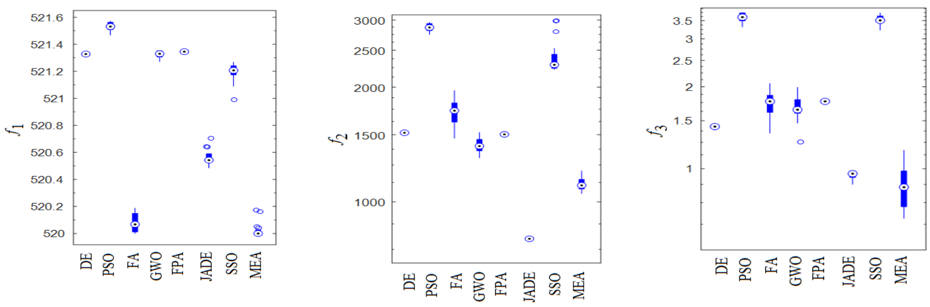
4 Results Analysis

The results for six unconstrained benchmarks of the IEEE CEC2014 competition [8] for dimension D equal to 100 are summarized in Figure 2.

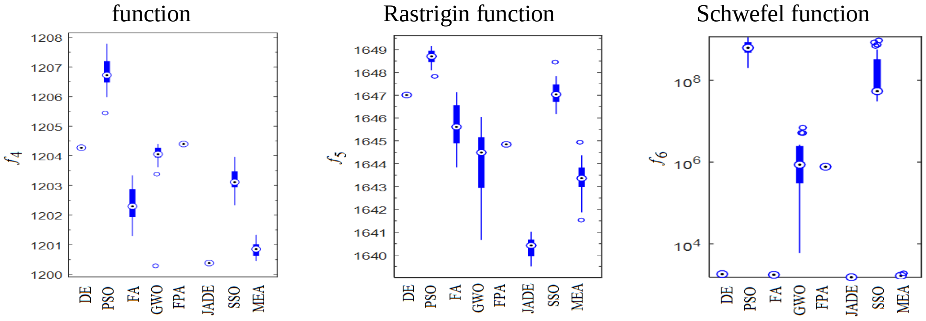
One can see that for the shifted and rotated Ackley function on Figure 2(a), MEA has presented the best median value, having some of outlier results near to FA. For the second problem tested, shifted and rotated Rastrigin function, presented on Figure 2(b), the best median results were reached by JADE, however MEA had the second best performance, showing also a small quartiles and percentiles span.

The third problem tested was the shifted and rotated Schwefel function. Its results can be checked on Figure 2(c). MEA has presented the best median performance and its results can only be compared to JADE when the result dispersion is taken into account. MEA achieved the second best median result for the shifted and rotated Katsuura function, shown on Figure 2(d). JADE presented the best median value for that problem and the GWO had an outlier better than the MEA results for one run.

Shifted and rotated expanded Scaffer function best median value was achieved by JADE, as shown in Figure 2(e). MEA had presented the second best median results, and if the result dispersion is taken into account the GWO results can be within MEA range. The last problem tested is a composition of two benchmark functions and its results can be seen on Figure 2(f). One can see that DE, FA, JADE and MEA achieved comparable performance in terms of median objective function values, however MEA presented two worse outliers.



(a) shifted and rotated Ackley function (b) shifted and rotated Rastrigin function (c) shifted and rotated Schwefel function



(d) shifted and rotated Katsuura function (e) shifted and rotated expanded Scaffer function (f) Griewank+Rosenbrock function

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

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5 Conclusion and future research

In this paper, we propose a new bio-inspired MEA to solve global optimization problems with continuous variables. This new method has only one parameter that stands for the initial population size. In the current work, the performance of MEA method is experimentally tested only using six benchmark optimization problems. This paper is a preliminary study opening up a wide range of possibilities for further improvement and extension. In the future research, we will apply the proposed MEA and its multiobjective form to solve large-scale optimization case studies.

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