Journal of Hyperstructures 5 *(2) (2016), 169-181.*
ISSN: 2322-1666 print/2251-8436 online

A NOVEL METAHEURISTICS FOR OPTIMIZATION INSPIRED BY MOTHER-INFANT COMMUNICATION IN ANIMAL COLONIES

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Abstract. Mother-infant vocalization from distance in some animal species such as bats, gulls and penguins is a basic tool to find the other's location. It is referred to echolocation or bio-sonar characteristics which is important for the mother to find exactly its own baby in a large colony. Moreover, the baby uses it to better conduction the mother in getting back to the nest without knowing its exact location. This natural fact is the motivation of the current study to devise a novel metaheuristic algorithm in solving optimization problems. The proposed methodology was tested on some continuous functions and led to promising results on convergence.

Key Words: Metaheuristics, Continuous optimization problem, Evolutionary Methods.
2010 Mathematics Subject Classification: Primary: 90C59; Secondary: 90C26.

1. Introduction

Nowadays, most of engineering challenges can be formulated as optimization problems, in discrete or continuous optimization form, for which there is no knowledge of an exact polynomial algorithm. A great number of heuristics were developed leading to a solution close to the optimum, the majority of them were convenient specifically for a given

Received: 26 August 2016, Accepted: 9 October 2016. Ahmad Yousefian Darani;
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problem. Moreover, some certain continuous optimization problems exist with the same property enabling to definitely locate a global optimum in a completed number of computations. For these kind of problems, there are significant tools of traditional methods. However, they are often ineffective if the objective function does not satisfy particular structural properties such as convexity and smoothness.

Metaheuristics which are usually nature-inspired and based on swarm intelligence, created developments on both domains. They are applied to almost all kinds of discrete problems as well as are adapted to the continuous problems. The ways for inspiration are such diverse, while all of them apply some specific characteristics in formulating the key updating formulae. To name some examples, genetic algorithm was inspired by Darwinian evolution characteristics of biological systems [6], the ant colony algorithm which employs their behavior when they are searching for a shortest path in their colony [1], particle swarm optimization is based on the swarming behavior of birds and fish [6], and firefly algorithm which was based on the flashing characteristics of tropical fireflies [7].

Recently, bat algorithm based on the echolocation features of microbats has been introduced [8], which employs a frequency-tuning technique to increase the diversity of the solutions in the population. At the same time, it uses the automatic zooming to balance exploration and exploitation during the search process by mimicking the variations of pulse emission rates and loudness of bats when searching for prey. We refer the interested reader for a through review of the literature to [9] and references within.

Natural characteristics of mother-infant vocalization in some animal species is an unknown feature in heuristic and metaheuristic algorithms literature. Let us explain this characteristics on some species. According to the observation on mother-infant reunion, the female adult bats only feed their own babies, but not the other's in the colony. The mother can recognize its own infant through both odor and vocal cues indicating that the isolation calls emitted by the infant bats play an important role in mother-infant communication [10]. Another example is *lesser spear-nosed bat* when the mother backs to her baby after separation. The calls of mother consists of a specific frequency-time structure, which marks its individually voice distinguishable by her infant [2]. An experimental study revealed that the *big brown bat* responds exclusively to sinusoidally frequency modulated signals [11]. In another conducted study, the spontaneous vocalization development of *greater horseshoe bat* was investigated. Vocalizations of the greater horseshoe bat infants could be categorized to those fulfilling as pathfinders of echolocation sounds and those serving as isolation calls used to inform their mothers.

Similar treatment is observed in *black-tailed gulls* in their reproductive colonies. Their different vocal signals can be categorized in three main groups which the contact call in the most used one as a tool in distinction between individuals, especially in between parents and chicks. The empirical research shows the importance of this call in social relationship in a high populated breeding colonies [5].

Analogously, in feeding of a chick with the *king penguin* the baby must recognize the call of its parents, mostly using the frequency, in the continuously noisy background of the colony. Experimental observations revealed that the chick's frequency analysis of the call is not tuned towards precise peak energy values, the signal being recognized even when the carrier frequency was shifted out of the prespecified range [3]. This structure is repeated through several repetition of the call giving a distinct vocal signature. The experiments also denoted that the small amount of information necessary to understand the message. The high redundancy in the time and frequency domains and the almost infinite possibilities of coding provided by the frequency modulation signature permit the chick to recognize the adult, without the help of a nest position.

This mysterious capability inspired us to develop a new metaheuristics which efficiently solves convex and nonconvex continuous problems to an (local) optimizer based on our experiments. There is a main difference between our methodology with the bat algorithm proposed in [8], though both can be considered as a frequency-tuning algorithm. There, the author considered a population of bats, each of them representing a potential optimal point of a given optimization problem. The optimal point is the position of the prey. Within an iteration, the algorithm selects the best place where one of the bats is according to the objective function value. Each bat emits a sound towards the prey with a randomly selected frequency in an interval and approximates a better direction towards the prey using its sound reflection. The loudness and the rate of pulse emission are updated. The updating factor treats as the cooling factor in simulated annealing. We restate that, there is no additional assumption on communicating information between the bats and the prey, but only the sound emitted by the bats and its reflection, the loudness of the voices and the pulse emission rates.

In our algorithm, instead of a population of bats, just a mother is considered which could be one of such species with a population of infants which are updated in each iteration. It is assumed that the mother was with its baby before leaving for prey. The focus in our algorithm is their policy to reuniting among a colony of mothers and babies may be of millions. The only device to communicate between the mother and its infant is echolocation sounds transmitting in a mutually pre-compromised range. They tune their voice frequencies in the range that is understandable for both. It is assumed that the infant stands in an optimal solution of the underlying objective function and the mother moves toward this point in each iteration. In this algorithm, voice loudness and pulse emission rates are not employed. To distinguish our algorithms with the one in [8], it is referred to as *Parent-Infant communication algorithm*.

The paper is organized as follows. Section 2 describes main assumptions and follows with deeply explanation of the algorithm. The convergence of the algorithms is analyzed superficially in this section. Section 3 has experimental results on some test problems. The performance of the algorithm is investigated for different values of parameters in Section 4. Final section includes some concluding remarks, future work direction as well as possible generalizations and developments.

2. Standard Parent-Infant Communication Algorithm

Based on the above description and characteristics of Mother-Infant echol- ocation, we developed the algorithm with the three idealized rules:

(1) All infants as well as the mother use echolocation to determine distance, and they also know the difference between each other and other barriers in some way.
(2) The mother as well as its infant emit voices with a frequency varying in $[f_{\min}, f_{\max}]$. The mother as well as its infant can automatically adjust the wavelength (or frequency) of their emitted pulses in this range.
(3) The mother has the ability to recognize its own infant's voice among the other's in an unknown way.

A pseudo-code of the proposed algorithm is presented in Algorithm 1. An iteration is described in the sequel.

2.1. **Virtual Mother-Infants Treatment.** A small number of infants are selected from the colony for which their positions are fixed. Only the mother's infant is in the optimal position of the given objective function which might be a local optimizer. For the infants population of the size n, the initial set $X(0) = \{(x_i(0), f_i(0))|i, 1, \ldots, n\}$ is considered, where $f_i(0) \in [f_{\min}, f_{\max}]$ is the emitted voice frequency of the i-th infant situated at $x_i(0)$.

Before separation of the mother and its infant, the mother memorize the initial frequency of their voices, and compute their ratio which is in an agreed interval. Let us denote this value by $K(0) = f_M(0)/f_B(0)$, where $f_M(0)$ and $f_B(0)$ are the voice frequency of the mother and the infant, respectively. They are randomly selected in $[f_{\min}, f_{\max}]$ at the start of algorithm. This value will be adjusted by them as the mother getting closer to its infant. It is observed that this ratio approaches to a limit point as the algorithm proceeds. In each iteration of the algorithm, the population of infants substituted by a new one until the prespecified number of iterations are performed.

2.2. **Virtual Mother Motion.** Let us describe the initial motion. The others are performed similarly. The mother first calculates the ratio $K_i(0) = f_M(0)/f_i(0)$ for $i = 1, \ldots, n$, selects the closest one to $K(0)$, and considers the corresponding infant say the jth one, as its own baby (i.e., x_j is a candidate for the optimal solution). Her current position is $x_0(0)$; she moves toward $x_j(0)$ along direction $d(0) = x_j(0) - x_0(0)$.and updates her position according to a line search for a smallest value of the objective function along way. This point will be considered as the mother's position at the next iteration and be denoted by $x_0(1)$ corresponding to the optimal step length α^*.

2.3. **Updates.** The updates in the first step are as follows. Analogous updates are considered at other iterations. First, the voice frequencies of the mother and of the infant are adjusted in terms of the objective function values at the initial and the updated positions of the mother. This could be carried out by a random process such as

$$f_M(1) = f_M(0) - \beta_M[F(x_1^*) - F(x_0)], \tag{2.1}$$

$$f_B(1) = f_B(0) - \beta_B[F(x_1^*) - F(x_0)], \tag{2.2}$$

where β_M and β_B are two random numbers in $(0, 1)$.

Furthermore, the mother disregards the current population of infants and considers a new set $X(1) = \{(x_i(1), f_i(1)) \mid i, 1, \ldots, n\}$. The position of each infant in $X(1)$ is selected at the decreasing side of the objective function. One possible choice could be the half space identified by the hyperplane passing through x_1^* and perpendicular to the vector $-d(0)$.

$$x_i(1) \in \text{Halfspace}(x_0(1), -d(0)). \tag{2.3}$$

The voice frequency of infants are chosen randomly, too. A potential update of the frequencies is as

$$f_i(1) = f_{\min} + \gamma(f_{\max} - f_{\min}),\ i = 1, \ldots, n, \tag{2.4}$$

where γ is a random value in $(0, 1)$.

3. Some Empirical Results

In this section the experimental results are presented and discussed. The examples are three of those in [8]. Similarly, the frequency variation range is fixed in $[0, 100]$, and $\beta_M = \beta_B$ and γ are randomly selected from a uniform distribution in $(0, 1)$. Moreover, a simple line search is implemented; the interval $[0, 1]$ containing α is divided into 10 subintervals and the one with the smallest value of the objective function among the associated 11 points is selected. The infants population of the size $n = 25$ and the iteration number 100 are assumed. In all figures the black dots are the random starting points and the red ones are the final points resulted by the algorithm. The algorithm is implemented in Matlab to visualize its effectiveness in practice. More experimental results are presented in the next section.

The first example considers a function with a unique global optimal solution.

Example 3.1. This function is a version of De Jong's standard sphere function with a single global minimum at $c = (c_1, \ldots, c_d)^T$.

$$h(x) = \sum_{i=1}^{d} (x_i - c_i)^2. \tag{3.1}$$

In 2D, $c_1 = -10$ and $c_2 = 30$ are considered and consequently the optimal solution is $(-10, 30)$. In our experiment, it was observed that the starting point is unimportant in the efficiently convergence of the algorithm. The right figure in Fig. 1 denotes the trace of produced points converging to the optimal solution (denoted by blue +'s). The left one depicts the starting points and resulting ones for 50 runs of the algorithm.

Data: Objective function $F(x)$;
Initial position x_0 of the mother;
Permitted frequency range $[f_{\min}, f_{\max}]$;
Randomly selected $f_M(0), f_B(0) \in [f_{\min}, f_{\max}]$;
Number of selected infants population by the mother during each iteration,
denoted by n;
Initialization;
$t = 0$;
Compute $K(t) = f_M(t)/f_B(t)$;
Infants population with their positions and emitted frequencies
$X(0) = \{(x_i(0), f_i(0)) \mid i, 1, \dots, n\}$, with $f_i(0) \in [f_{\min}, f_{\max}]$;
Max Iteration $= \tau$;
$\beta_M, \beta_B, \gamma \in [0, 1]$;
while $t < \tau$ **do**
  Compute $K_i(t) = f_M(t)/f_i(t)$, $i = 1, \dots, n$;
  Find $j = \text{argmin}\{|K_i(t) - K(t)|\}$;
  Compute the motion direction $d(t) = x_j(t) - x_0(t)$;
  Define $x(\alpha) = x_0(t) + \alpha d(t)$;
  Run a line search $\alpha(t) = \text{argmin}_{\alpha \in [0,1]} F(x(\alpha))$;
  update;
  Mother's position as $x_0(t+1) = x_0(t) + \alpha(t)d(t)$;
  Mother's voice frequency based on (2.1) ;
  Infant's voice frequency based on (2.2) ;
  New infants population
  $X(t+1) = \{(x_i(t+1), f_i(t+1)), i = 1, \dots n\}$ based on (2.3) and (2.4);
  $t := t + 1$
end
Result: The local (global) optimizer $x_(\tau)$.

Algorithm 1: Mother-Infant communication algorithm.

At the next example, a function with multiple minimizers with no local ones is considered.

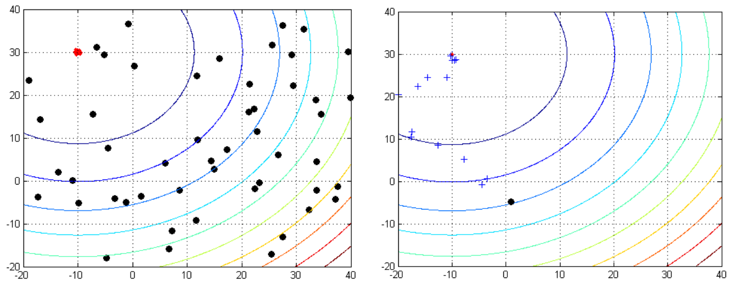

FIGURE 1. Results for the De Jong's standard sphere function in $d = 2$. The right figure denote one sample starting point, trace of intermediates and the final. The left one denotes the results for 50 runs of the algorithm, stating points and the accumulating one.

Example 3.2. Consider the Rosenbrock's function as follows

$$f(x) = \sum_{i=1}^{d-1}(1 - x_i^2)^2 + 100(x_{i+1} - x_i^2)^2. \tag{3.2}$$

Analogues to [8], the box containing the optimal solutions is considered as $B = \{x \mid , -2.048 \leq x_i \leq 2.048, i = 1, \ldots, d\}$. This function has two global minimizers $(1, 1)$ and $(-1, 1)$ in 2D and the results of 50 runs are depicted in Fig 2. It is seen that each of the two global optimizers could be the accumulation point of the algorithm. The right one has a concentrated insight to the global optimizers $(-1, 1)$ and $(1, 1)$.

From Fig. 3, it is obvious that the position of starting points is ineffective to the resulting point of the algorithm. In these both runs, the starting point is closer to $(1, 1)$ than to $(-1, 1)$. However, the final points are not the same. To avoid this treatment of the algorithm, when one of the optimizers is of special interest and its approximate position is known, the starting point box B can be accordingly shrunk. Experiments certificate this approach for the mentioned drawback. However, it was observed in some runs of the algorithm, when the starting point has been selected enough close to one of the optimums, it stopped at the other one.

Last test function has has a global minimizer at the origin with some local minimizers in its proximity.

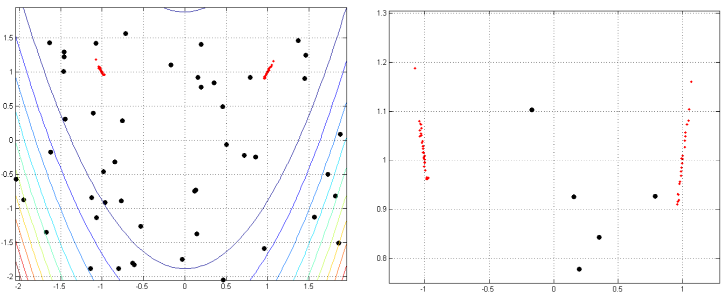

FIGURE 2. The left plot denotes the results of running of the algorithm on the Rosenbrock's function in 2D. The right one depicts the resulting points of the algorithm.

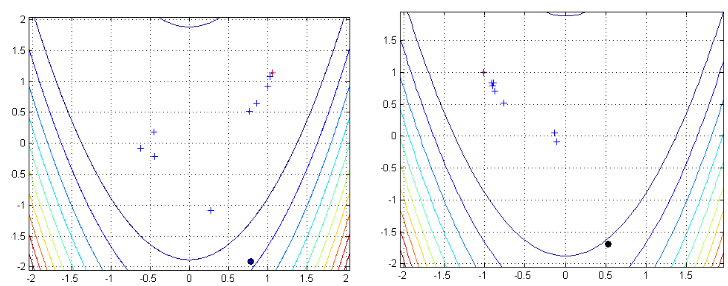

FIGURE 3. Two samples of runs, each of them is approaching to one of the two global optimal solutions of the Rosenbrock's function for $d = 2$.

Example 3.3. Let us consider the Eggcrate function in 2D as

$$g(x, y) = x^2 + y^2 + 25(\sin^2 x + \sin^2 y), \ -2\pi \leq x, y \leq 2\pi. \tag{3.3}$$

Fig. 4 depicts the algorithm behavior on this problem. The right one shows the situation when the algorithm converges to the global minimum regardless of the initial point's position. In addition, it was observed that when the infants population size is lest than 25 and the iterations number is not more than 50, the resulting point is trapped at a local minimizer.

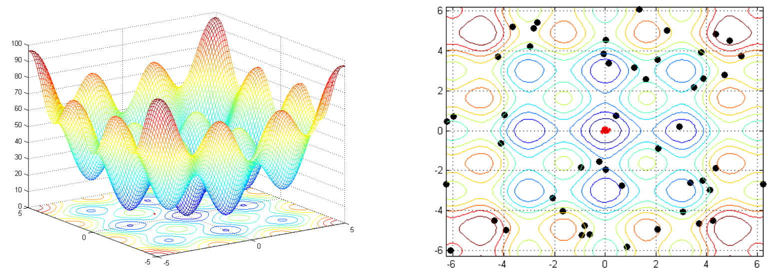

FIGURE 4. The left figure denote the Eggcrate function $g(x, y)$ plotted in the box $[-2\pi, 2\pi] \times [-2\pi, 2\pi]$. The right one depicts the results on 50 times running the algorithm. Black circles are the random starting points and the red dots are the resulting points.

4. Convergence Analysis

To better realize the convergence behavior of the algorithm, rigorous computation were conducted on these examples. The number of iterations was considered in the range of $30 - 100$ for the De Jong's standard sphere function and the Rosenbrock's function. It was fixed from 50 to 150 for the Eggcrate function. In all cases, infants population size was considered $n = 100$. The absolute value of difference between the objective value at the resulting point of the algorithm and the exact value is computed for each iteration number and the average of them was noted. Based on experiments, as the number of iteration (number of mother's steps toward the infant) increases, the convergence of the algorithm is better observed.

For the case when there is a unique global optimum and no local optimizers exist, the algorithm behaves expectedly. Strictly convex optimization problems fall in this category. It is important to state that in this algorithm neither the convexity assumption nor the smoothness is considered. The results for $d = 2, 4, 8, 6$ of the De Jong's standard sphere function are depicted in Fig. 5.

Recall that the Rosenbrock's function has two global optimum for $d = 2$, but there is no local optimizer. Analogously, With increasing the number of iteration, the results are getting more accurate. Fig. 6 denotes the results for $d = 2, 4$ and reveal that for the small number of iteration in high dimensional cases, the rate of convergence is low.

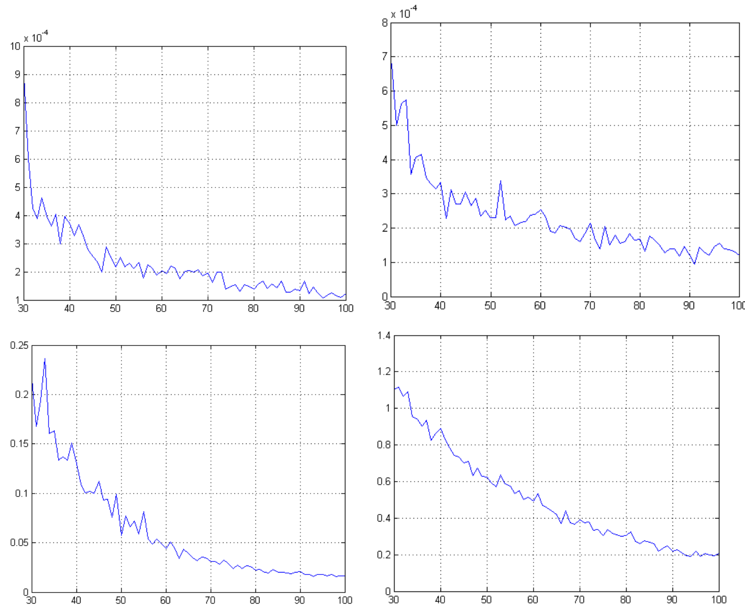

FIGURE 5. The running results on De Jong's standard sphere function for $d = 2, 4, 8, 16$ and iteration numbers from 30 to 100.

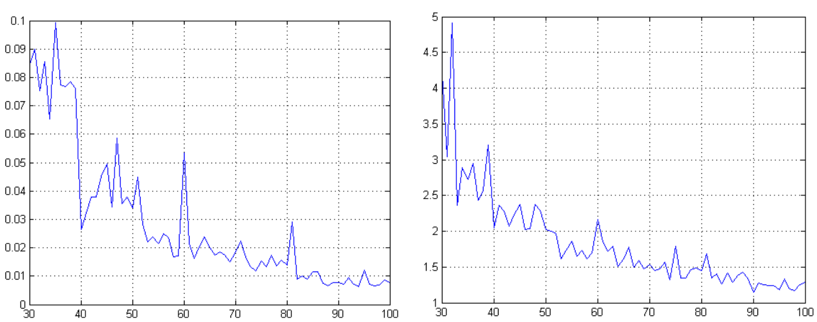

FIGURE 6. The running results on the Rosenbrock's function for $d = 2, 4$ and iteration numbers from 30 to 100.

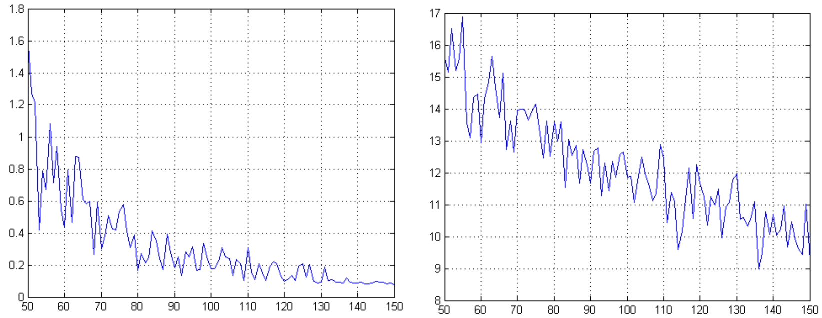

FIGURE 7. The running results on the Eggcrate function for $d = 2, 4$ and iteration numbers from 50 to 150.

Experiments for the function with many local optimums such as the Eggcrate function denote that knowing approximate position of the global optimum can help to narrow the search region, otherwise, the algorithm may be trapped in a local optimum. Fig. 7 depicts the results for $d = 2, 4$ on the Eggcrate function and iteration numbers from 50 to 150. Here, convergence treatment of the algorithm is carried out for the global optimizer.

5. Concluding Remarks

A novel meta-huristic method was presented in this report. The test problems examined were unconstrainted. Experimental results are promissing in genneral. However, further computation have to be carried out to examin the effect of infants population size on the convergence. For the constrained cases, one may choose the position of infants which satisfy these constraints. Selecting a feasible solution in this case might be a challenge. Our presented algorihm is a continoues version and binary case migth be of more interest which is our future study direction.

In the implemetation, a simple line search is considered between the curren position of the mother and the best one's in the selected population. One may consider exact line search methods instead if the problem is well-behaved. For a general case, Armijo rule and Golden section search are the two [4] to name.

To update the infants population in each iterateion, a simple method was employed to detect a possible decreasing direction for the objective function in the search space. Other possiblities such as steepest descent direction can be considered when the objective function is smooth.

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