Chimp Optimization Algorithm

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M. Khishe, M. R. Mosavi

***Abstract*—This article proposes a novel metaheuristic algorithm called Chimp Optimization Algorithm (ChOA) inspired by the individual intelligence and sexual motivation of chimps in their group hunting, which is different from the other social predators. ChOA is designed to further alleviate the two problems of slow convergence speed and trapping in local optima in solving high-dimensional problems such as a learning algorithm for high-dimension neural network. In this article, a mathematical model of diverse intelligence and sexual motivation is proposed. Four types of chimps entitled attacker, barrier, chaser, and driver are employed for simulating the diverse intelligence. Moreover, the four main steps of hunting, driving, blocking, and attacking, are implemented. Afterward, the algorithm is tested on 30 well-known benchmark functions, and the results are compared to four newly proposed meta-heuristic algorithms in term of convergence speed, the probability of getting stuck in local minimums, and the accuracy of obtained results. The results indicate that the ChOA outperforms the other benchmark optimization algorithms.**

***Index Terms*—Chimp, mathematical model, metaheuristic, optimization.**

I. CHIMP OPTIMIZATION ALGORITHM

This section presents and discusses the inspiration of ChOA method. Afterwards, it provides the mathematical model of the proposed algorithm.

A. Inspiration

Chimps (sometimes called Chimpanzees) are one of two merely African species of great ape. They are as much as the closest to the humans' living relatives. As shown in Fig. 1, the chimps, as well as the dolphins, have the most similar Brain to Body Ratio (BBR) to humans. As discussed in [75] mammals with relatively larger BBR are mostly assumed to be smarter. The chimp and the human DNA are so similar because they are descended from a single ancestor species (Hominoid) that lived seven or eight million years ago. Fig. 2 indicates the phylogeny of super-family Hominoid [76]. As shown in Fig. 3, these two species share a 98.8 percent of their DNAs [77].

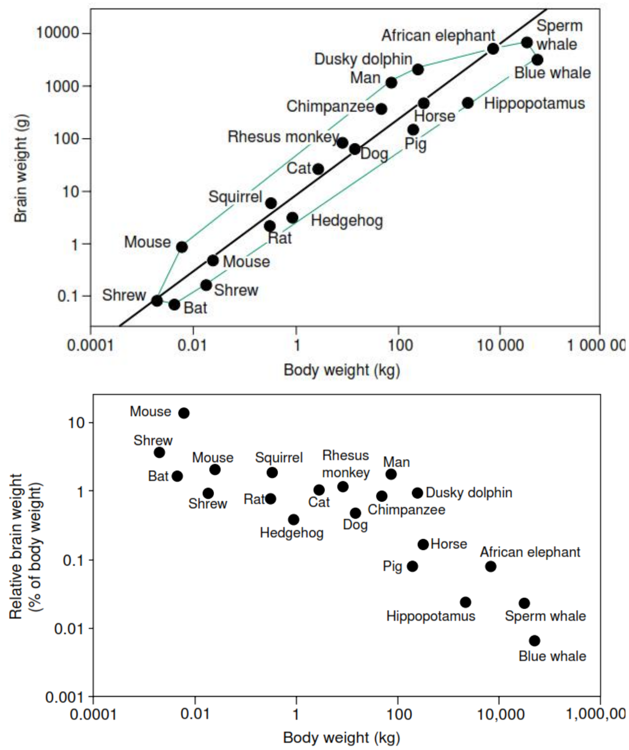

Fig. 1. Two different plot of relationship between body size and brain size in various mammals [75].

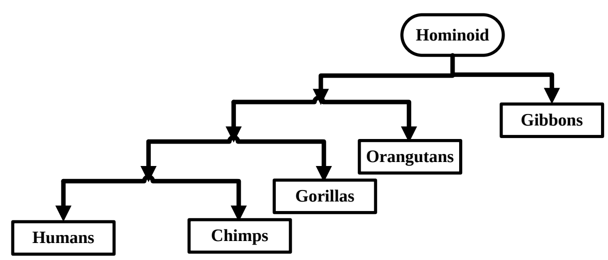

Fig. 2. Phylogeny of super-family Hominoid.

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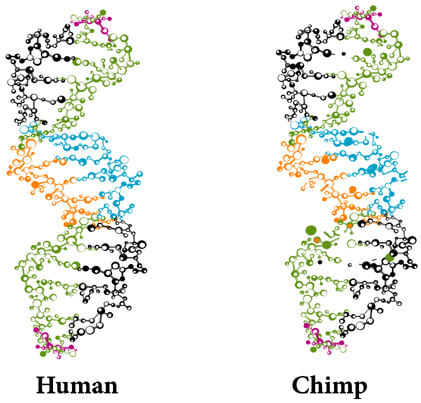


Fig. 3. Human and chimp DNA.

The chimp's colony is a fission-fusion society. This kind of society is one in which the combination or size of the colony changes as time passes and members move throughout the environment. For chimps that live in fission-fusion colonies, group composition is a dynamic property [78]. Considering these issues, the independent group concept is proposed. In this technique, each group of the chimps independently attempts to discover the search space with its own strategy. In each group, chimps are not quite similar in terms of ability and intelligence, but they are all doing their duties as a member of the colony. The ability of each individual can be useful in a particular situation.

In a chimp colony, there are four types of chimps entitled driver, barrier, chaser, and attackers. They all have different abilities, but these diversities are necessary for a successful hunt. Drivers follow the prey without attempting to catch up with it. Barriers place themselves in a tree to build a dam across the progression of the prey. Chasers move rapidly after the prey to catch up with it. Finally, attackers prognosticate the breakout route of the prey to infliction it (the prey) back towards the chasers or down into the lower canopy. These steps of hunting process are shown in Fig. 4. Attackers are thought to need much more cognitive endeavor in prognosticating the subsequent movements of the prey, and they are thus remunerated with a larger piece of meat after a successful hunt. This important role (attacking) correlates positively with the age, smartness, and physical ability. Moreover, chimps can change duties during the same hunt or keep their same duty during the entire process [79].

It has been proven that chimps hunt to obtain meat for trading in social favors such as coalitionary support, sex or grooming [74]. So, by opening up a new realm of privileges, smartness may have an indirect effect on hunting. To the best of our knowledge, in addition to humans, this "social incentives" has been proposed only for chimps. Hence, it would represent a critical difference between chimps and other social predators that depend on cognitive ability. This social incentive (sexual motivation) causes the chimps to act chaotically in the final stage of hunting process so that all chimps abandon their special duties and they try to get meat, frantically. Generally speaking, the hunting process of chimps is divided into two main phases: "Exploration" which consists of driving, blocking and chasing the prey and "Exploitation" which consists of attacking the prey. These two phases are shown in Fig.s 4 and 5, respectively. Then, all of these concepts of ChOA are mathematically formulated in the following section.

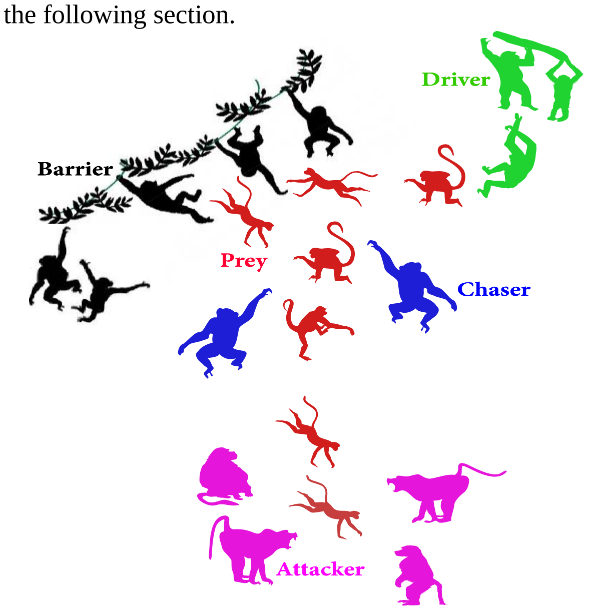


Fig. 4. The first phase of hunting process ("exploration").

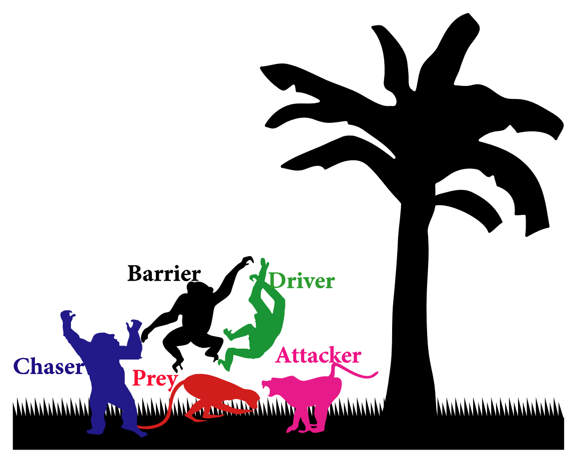


Fig. 5. The second phase of hunting process ("exploitation ").

B. *Mathematical Model and Algorithm*

In this section, mathematical models of independent group, driving, blocking, chasing and attacking are presented. Corresponding ChOA algorithm is then specified.

1) *Driving and Chasing the Prey*

As mentioned above, the prey is hunted during the exploration and exploitation phases. To mathematically model driving and chasing the prey, Eq.s (1) and (2) are proposed.

$$\mathbf{d} = \left| \mathbf{c}.\mathbf{x}_{\text{prey}}(t) - \mathbf{m}.\mathbf{x}_{chimp}(t) \right| \quad (1)$$

$$\mathbf{x}_{chimp}(t+1) = \mathbf{x}_{\text{prey}}(t) - \mathbf{a}.\mathbf{d} \quad (2)$$

Where t indicates the number of current iteration, **a, m,** and **c** are the coefficient vectors, $\mathbf{x}_{\text{prey}}$ is the vector of prey position and $\mathbf{X}_{chimp}$ is the position vector of a chimp. **a**, **m**, and $\mathbf{c}$ vectors are calculated by the Eq.s (3), (4) and (5), respectively.

$$\mathbf{a} = 2.\mathbf{f}.\mathbf{r}_1 - \mathbf{f} \quad (3)$$

$$\mathbf{c} = 2.\mathbf{r}_2 \quad (4)$$

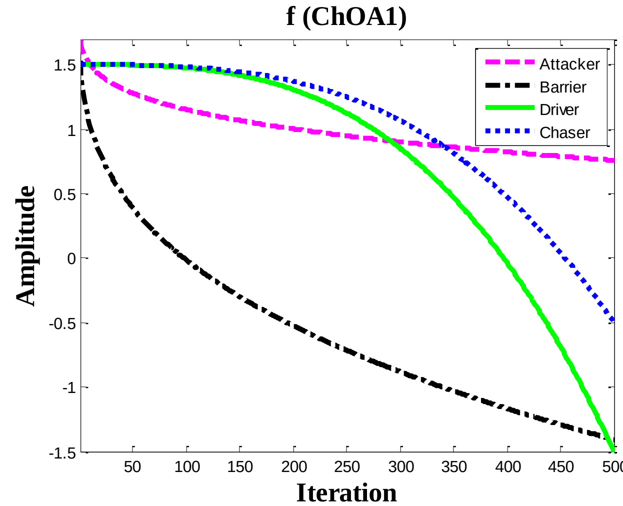
$$\mathbf{m} = \mathbf{Chaotic\_value} \quad (5)$$

In which, **f** is reduced non-linearly from 2.5 to 0 through the iteration process (in both exploitation and exploration phase). $\mathbf{r}_1$ and $\mathbf{r}_2$ are the random vectors in the range of [0,1]. Finally, **m** is a chaotic vector calculated based on various chaotic map so that this vector represents the effect of the sexual motivation of chimps in the hunting process. A full description of this vector will be described in detail in subsection 5. In the conventional population-based optimization algorithm, all particles have similar behavior in local and global searches so that the individuals can be considered as a single group with one common search strategy. However, theoretically, in every population-based optimization algorithm, different independent groups that have a common goal can be used to have a direct and random search result at the same time. In the following, independent groups of chimp using different strategies to update **f** will be modeled mathematically. Updating the independent groups can be implemented by any continuous function. These functions must be chosen in such a way that during each iteration **f** is reduced [80].

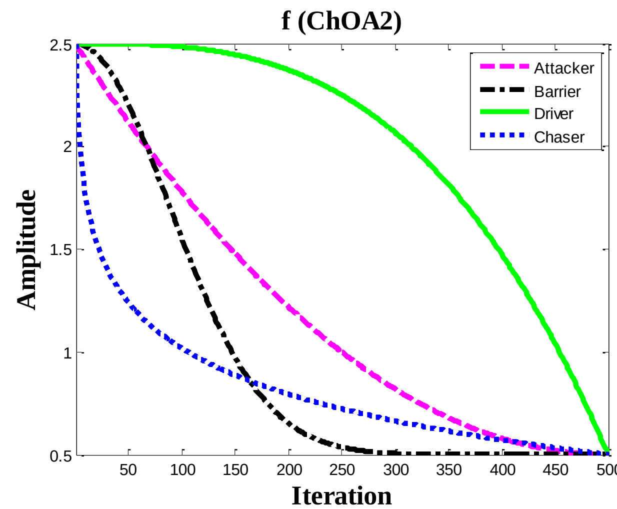
These four independent groups use their own patterns to search the problem space locally and globally. Also among various strategies which have been tested, two different versions of ChOA with various independent groups called ChOA1 and ChOA2 are selected to have the best performance in the benchmark optimization problems. The dynamic coefficients of **f** have been proposed in Table I and Fig. 6. In this table, T represents the maximum number of iterations, and t indicates the current iteration. These dynamic coefficients have been chosen with various curves and slopes so that each independent group has specific searching behavior for the sake of improving the performance of ChOA.

TABLE I
THE DYNAMIC COEFFICIENTS OF **f** VECTOR.

Groups	ChOA1	ChOA2
Group1	$1.95-2t^{1/4}/T^{1/3}$	$2.5-(2\log(t)/\log(T))$
Group2	$1.95-2t^{1/3}/T^{1/4}$	$(-2t^3/T^3)+2.5$
Group3	$(-3t^3/T^3)+1.5$	$0.5+2\exp[-(4t/T)^2]$
Group4	$(-2t^3/T^3)+1.5$	$2.5+2(t/T)^2-2(2t/T)$



(a) ChOA1



(b) ChOA2

Fig. 6. Mathematical models of dynamic coefficients (**f**) related to independent groups for (a) ChOA1 and (b) ChOA2.

Some points may be considered to understand how independent groups are effective in ChOA:

- Independent groups have different strategies to update **f**, so chimps could explore the search space with different capability.
- Diverse and dynamic strategies of **f** cause balancing between global and local search.
- Independent groups contain non-linear strategies such as logarithmic and exponential functions for **f**, so ChOA could be effective in solving complex optimization problems.
- ChOA with independent groups could be adaptable in solving a wider range of optimization problems.

To understand the effects of Eq.s (1) and (2), a two-dimensional representation of the position vector and a number of possible neighbors are shown in Fig. 7*a*. As can be observed, a chimp in position (x,y) can change its position with respect to prey's (x^*,y^*) location. Various locations around the most suitable agent can be taken considering its current location and changing and setting the values of **a** and **c** vectors. For instance the location of (x^*-x, y^*) is obtained by setting **a**=(1,0), **m**=(1,1) and **c**=(1,1). Updated possible locations of a chimp in a three-dimensional space are indicated in Fig. 7b. It should be noted that the chimps are allowed to access any position between the points shown in Fig. 7 through the random vectors $\mathbf{r}_1$ and $\mathbf{r}_2$. So, any chimp can randomly change its location within the space surrounding the prey using Eq.s (1) and (2).

This concept can be generalized to an n-dimensional search space. As mentioned in the previous section, the chimps also attack the prey with the chaotic strategy. This method is mathematically formulated in the following section.

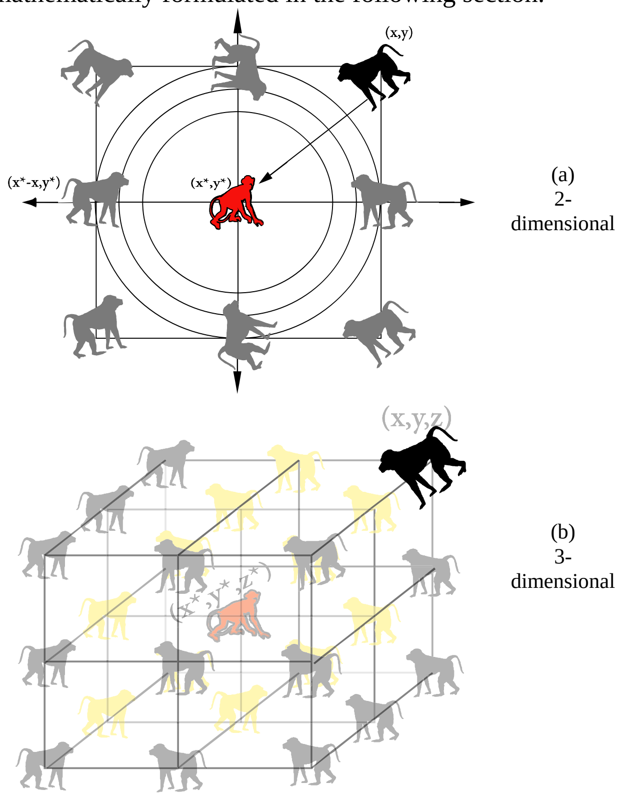


Fig. 7. Two and three-dimensional position vectors and their possible next locations.

2) Attacking Method (Exploitation Phase)

To mathematically model attacking behavior of chimps, two approaches are designed as follows: The chimps are capable of exploring the prey's location (by driving, blocking and chasing) and then encircling it. The hunting process is usually conducted by attacker chimps. Driver, barrier and chaser chimps are occasionally participate in the hunting process. Unfortunately in an abstract search space there is no information about the optimum location (prey). In order to mathematically simulate the behavior of the chimps, it is assumed that the first attacker (best solution available), driver, barrier and chaser are better informed about the location of potential prey. So, four of the best solutions yet obtained is stored and other chimps are forced to update their positions according to the best chimps locations. This relationship is expressed by the Eq.s (6), (7) and (8).

$$\begin{aligned}\mathbf{d}_{Attacker} &= |\mathbf{c}_1\mathbf{x}_{Attacker} - \mathbf{m}_1\mathbf{x}|, \quad \mathbf{d}_{Barrier} = |\mathbf{c}_2\mathbf{x}_{Barrier} - \mathbf{m}_2\mathbf{x}|,\\ \mathbf{d}_{Chaser} &= |\mathbf{c}_3\mathbf{x}_{Chaser} - \mathbf{m}_3\mathbf{x}|, \quad \mathbf{d}_{Driver} = |\mathbf{c}_4\mathbf{x}_{Driver} - \mathbf{m}_4\mathbf{x}|.\end{aligned} \tag{6}$$

$$\begin{aligned}\mathbf{x}_1 &= \mathbf{x}_{Attacker} - \mathbf{a}_1(\mathbf{d}_{Attacker}), \quad \mathbf{x}_2 = \mathbf{x}_{Barrier} - \mathbf{a}_2(\mathbf{d}_{Barrier}),\\ \mathbf{x}_3 &= \mathbf{x}_{Chaser} - \mathbf{a}_3(\mathbf{d}_{Chaser}), \quad \mathbf{x}_4 = \mathbf{x}_{Driver} - \mathbf{a}_4(\mathbf{d}_{Driver}).\end{aligned} \tag{7}$$

$$\mathbf{x}(t+1) = \frac{\mathbf{x}_1 + \mathbf{x}_2 + \mathbf{x}_3 + \mathbf{x}_4}{4} \tag{8}$$

Fig. 8 shows the process of updating the search chimp's location in two-dimensional search space regarding the position of other chimp positions. As it can be seen, the final position is located randomly in a circle which is defined by attacker, barrier, chaser and driver chimp positions. In other words, the prey position is estimated by four best groups and other chimps randomly update their positions within its vicinity.

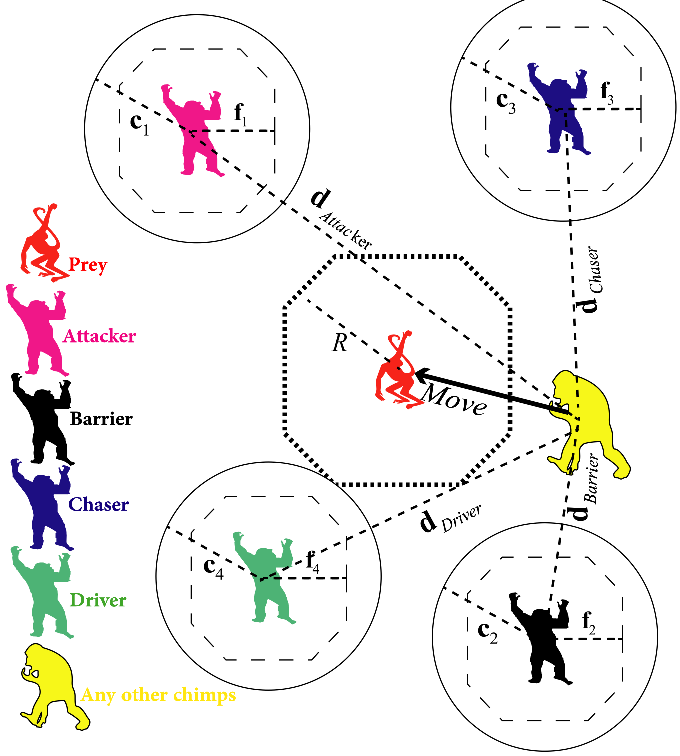


Fig. 8. Position updating in ChOA.

3) Prey Attacking (Utilization)

As mentioned previously, in the final stage, the chimps will attack the pray and finish the hunt as soon as the prey stops moving. To mathematically model the attacking process, the value of **f** should be reduced. Note that the variation range of the **a** is also reduced by **f**. In other words, **a** is a random variable in the interval of [-2**f**,2**f**], whereas the value of **f** reduces from 2.5 to 0 in the period of iterations. When the random values of **a** lie in the range of [-1,1], the next position of a chimp can be in any location between its current position and the position of the prey. Fig. 9 shows that the inequality $|\mathbf{a}|<1$ forces the chimps to attack the prey.

According to the operators that have already been presented, ChOA allows the chimps to update their positions according to the positions of attacker, barrier, chaser, and driver chimps and attack the prey. However, ChOAs may still be at the risk of trapping in local minima, so other operators are required to avoid this issue. Although, the proposed driving, blocking, and chasing mechanism somehow shows exploration process, ChOA requires more operators to emphasize exploration phase.

4) Searching for Pray (Exploration)

As previously mentioned, the exploration process among the chimps is mainly done considering the location of attacker, barrier, chaser, and driver chimps. They diverge to seek for the prey and aggregate to attack prey. In order to mathematically model the divergence behavior, the **a** vector with a random value bigger than 1 or smaller than -1 is used, so that the search agents are forced to diverge and get distant from prey. This procedure shows the exploration process and allows the ChOA to search globally. Fig. 9 shows that the inequality $|\mathbf{a}| > 1$ forces the chimps to scatter in the environment to find a better prey. This section is inspired from GWO [64].

Another ChOA component that affects the exploration phase is the value of **c**. As in Eq. (4), **c** vector elements are random variables in the interval of [0,2]. This component provides random weights for prey to reinforce (**c**>1) or lessen (**c**<1) the effect of prey location in the determination of the distance in Eq. (5). It also helps ChOA to enhance its stochastic behavior along the optimization process and reduce the chance of trapping in local minima. **c** is always needed to generate the random values and execute the exploration process not only in the initial iterations, but also in the final iterations. This factor is very useful for avoiding local minima, especially in the final iterations. **c** vector is also considered as the influence of the obstacles which prevent chimps from approaching the prey in nature. In general, natural obstacles in the path of chimps prevent them from approaching the prey with proper speed. This is the precise expression of the **c** vector effect. Depending on chimp's position, the **c** vector can assign a random weight to prey in order to make the hunt harder or easier.

5) Social Incentive (Sexual Motivation)

As mentioned previously, acquiring meet and subsequent social motivation (sex and grooming) in the final stage causes chimps to release their hunting responsibilities. Therefore, they try to obtain meat forcefully chaotic.

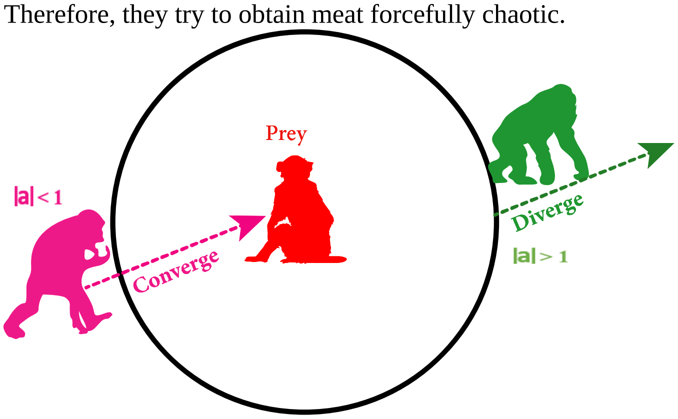


Fig. 9. Position updating mechanism of chimps and effects of |**a**| on it.

This chaotic behavior in final stage helps chimps to further alleviate the two problems of entrapment in local optima and slow convergence rate in solving high-dimensional problems.

The chaotic maps which have been used to improve the performance of ChOA are explained in this section. Six chaotic maps have been used in this article as shown in Table II and Fig. 10. These chaotic maps are deterministic processes which also have random behavior. In this article, value 0.7 has been considered as the primary point of all the maps in accordance with reference [81]. To model this simultaneous behavior, we assume that there is a probability of 50% to choose between either the normal updating position mechanism or the chaotic model to update the position of chimps during optimization. The mathematical model is expressed by Eq. (9).

$$\mathbf{x}_{chimp}(t+1) = \begin{cases} \mathbf{x}_{\text{prey}}(t) - \mathbf{a.d} & if \quad \mu < 0.5 \\ \textbf{Chatic\_value} & if \quad \mu > 0.5 \end{cases} \tag{9}$$

Where μ is a random number in [0,1].

TABLE II
CHAOTIC MAPS.

No	Name	Chaotic map	Range
1	Quadratic	$x_{i+1} = x^2_i - c\,,\ \text{c=1}$	(0,1)
2	Gauss /mouse	$x_{i+1} = \begin{cases} 1 & x_i = 0 \\ \dfrac{1}{\text{mod}(x_i,1)} & \text{otherwise} \end{cases}$	(0,1)
3	Logistic	$x_{i+1} = \alpha x_i(1-x_i), \quad \alpha=4$	(0,1)
4	Singer	$x_{i+1} = \mu(7.86x_i - 23.31x_i^2 + 28.75x_i^3 - 13.302875x_i^4)$, $\mu = 1.07$	(0,1)
5	Bernoulli	$x_{i+1} = 2x_i \ (mod\ 1)$	(0,1)
6	Tent	$x_{i+1} = \begin{cases} \dfrac{x_i}{0.7} & x_i < 0.7 \\ \dfrac{10}{3}(1-x_i) & 0.7 \le x_i \end{cases}$	(0,1)

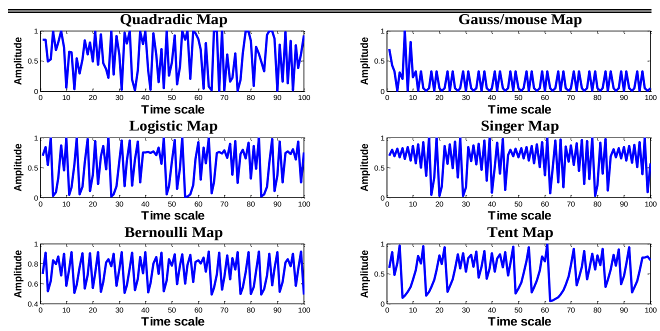


Fig. 10. The chaotic maps used in the article.

In brief, the searching process in ChOA begins with generating a stochastic population of chimps (candidate solutions). Then, all chimps are randomly divided into four predefined independent groups entitled attacker, barrier, chaser and driver. Each chimp updates its **f** coefficients using the group strategy. During the iteration period, attacker, barrier, chaser and driver chimps estimate the possible prey locations. Each candidate solution updates its distance from the prey. Adaptive tuning the **c** and **m** vectors cause local optima avoidance and faster convergence curve, simultaneously. The value of **f** is reduced from 2.5 to zero, to enhance the process of exploitation and attacking the prey. The inequality $|\mathbf{a}|>1$ results in divergence of the candidate solutions, otherwise, they eventually converge toward the prey. Fig. 11 presents the pseudo-code of ChOA.

```
Algorithm: ChOA
Initialize the chimp population x_i (i=1,2, ...,n)
Initialize f, m, a and c
Calculate the position of each chimp
Divide chimps randomly into independent groups
Until stopping condition is satisfied
Calculate the fitness of each chimp
x_Attacker=the best search agent
x_Chaser=the second best search agent
x_Barrier=the third best search agent
x_Driver=the fourth best search agent
  while (t < maximum number of iterations)
      for each chimp:
          Extract the chimp's group
          Use its group strategy to update f, m and c
          Use f, m and c to calculate a and then d
      end for
          for each search chimp
                  if (μ <0.5)
                          if (|a| < 1)
                Update the position of the current search agent by the Eq.
(2)
                          else if (|a|>1)
                                 Select a random search agent
                          end if
                  else if (μ >0.5)
                Update the position of the current search by the Eq.(9)
                  end if
          end for
     Update f, m, a and c
     Update x_Attacker, x_Driver, x_Barrier, x_Chaser
     t=t+1
   end while
return x_Attacker
```

Fig. 11. Presents the pseudo-code of ChOA.

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The source code is available:

https://se.mathworks.com/matlabcentral/fileexchange/76763-chimp-optimization-algorithm