Moth-Dolphin Optimization Algorithm: A Nature Inspired Technique

Amit Kumar, Sanjay Singla, Meenakshi Sharma, Shakti Kundu

Abstract: This paper proposes a moth-dolphin based nature inspired optimization algorithm. This algorithm embeds the communication behavior of dolphin to Moth. The Moth route towards moon through the moon light in an optimized manner. But each moth doesn't follow optimized path to travel towards the moon. The communication among the moth enables them to follow the best path towards moon. Thus, moth-dolphin algorithm uses the communication between moths to enhance the performance. The Moth–dolphin is an optimization algorithm which uses the exploration as well as exploitation search to achieve the global optima. The performance comparison of proposed algorithm with the moth-flame optimization algorithm, modified particle swarm optimization algorithm, differential evaluation and non-dominated sorting genetic algorithm over unimodal as well as multimodal functions ensures better results.

Keywords: Optimization, Moth, Moth-flame, Dolphin, Global Optima.

I. INTRODUCTION AND MOTIVATION FOR RESEARCH

Optimization is a technique to find the global optima i.e. best solution(s) possible for any particular problem. The complexity of problems is increasing everyday due to the advancement of technology. Initially the optimization problems are solved mathematically but this leads to the convergence towards local optima. This requires new optimization algorithms to avoid local optima and move towards the global optima. The new optimization algorithms use the heuristic search to avoid the local optima. The current researches suggest using the natural computing for the heuristic search [1].

Natural Computing is a field of research that declarations against the specialization of orders in science. It appears, with its three principle regions of examination, that information from different fields of research are important for a superior comprehension of life, for the review and reproduction of characteristic frameworks and forms, and for the proposition of novel registering ideal models.

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Physicists, scientific experts, engineers, researcher, PC researchers, among others, all need to act together or possibly share thoughts and information with a specific end goal to make normal registering practical.

The greater part of the computational methodologies common processing manages depends on exceedingly streamlined variants of the instruments and procedures introduce in the comparing normal wonders. The purposes behind such improvements and deliberations are complex. As a matter of first importance, most disentanglement is important to make the calculation with an extensive number of elements tractable. Likewise, it can be profitable to highlight the insignificant components important to empower some specific parts of a framework to be recreated and to watch some eminent properties. These eminent properties lead to the use of the nature inspired algorithms for heuristic search. So, nature inspired techniques can be used for optimization [2].

Various nature inspired methodologies has been given by distinct investigators are Moth-Flame Optimization Algorithm (MFOA) [1], Gravitational Search Algorithm (GSA) [3], Grey Wolf Optimizer (GWO) [4], Particle Swarm Optimization (PSO) [5], Genetic Algorithm (GA) [6],Differential Evolution (DE) [7] etc. GA exhibits the behavior of biological evolution, completes its optimization operation by using operators like mutation and crossover. Different modification GA has been investigated, one of them is Non-dominated Sorting genetic algorithm (NSGA). NSGA is a popular multi-objective EC algorithm that builds the next generation parent by ordering all existing level parents as well as offspring into separate level of non-dominated (ordered) solutions. This algorithm also preserves the diversity based on the crowding distance [8, 9]. The PSO demonstrate the motion of bird flock, the velocity and position updation phenomena of the bird flock are used for the optimization. Modified binary particle swarm optimization (MBPSO) is designed to deal with premature convergence of binary particle swarm optimization. It manages the particle inconsistency using the velocity and the resemblance between best particle solutions [10]. DE optimizes the problem by updating the candidate solution in lieu to a given measure of quality. The GSA uses the gravitational force fundamentals for the optimization purpose. The MFOA uses the moth-flame routing phenomenon to optimize any problem. The MFOA is described in the next section. The remaining paper has been classified in to four sections.

The next section covers the MFOA algorithm followed by the section containing detail of dolphin. Then moth-dolphin algorithm and its performance evaluation have been done in next two sections.

II. MOTH-FLAME OPTIMIZATION ALGORITHM

Moth is a type of butterfly and it uses the moon radiance (light) to route towards the moon. The routing of the moth comprises of straight as well as the spiral motion depending upon whether the moon(destination) is far or near from the current position of moth. This phenomenon of routing of the moth towards the moon can be used to in sensor network to transfer the data from source to the destination in an optimized manner [1]. This section describes the moth-flame optimization algorithm as follow

In the MFOA, n moths are travelling towards the moon in d dimensions then the position matrix can be given shown as eq. 1.

$$MP_c = \begin{bmatrix} MP_{1,1} & \cdots & MP_{1,v} \\ \vdots & \ddots & \vdots \\ MP_{nm,1} & \cdots & MP_{nm,v} \end{bmatrix}$$

(1)

The evaluation of the position of the moth can be done by using the objective (fitness) function and corresponding matrix is given in eq. (2).

$$FM_c = \begin{bmatrix} FM_1 \\ \vdots \\ FM_{mn} \end{bmatrix}$$

(2)

The best position in the matrix of equation (1) can be found by analyzing the corresponding values in eq. (2) (best solution can be minimum or maximum value depending upon the problem). The best position vector is the form of a matrix (known as flame matrix) displayed in eq. (3).

$$FP_c = \begin{bmatrix} FP_{1,1} & \cdots & FP_{nm,v} \\ \vdots & \ddots & \vdots \\ FP_{nm,1} & \cdots & FP_{nm,v} \end{bmatrix}$$

(3)

The corresponding values of the objective function in shown in the equation (4)

$$FP_c = \begin{bmatrix} FP_1 \\ \vdots \\ FP_{nm} \end{bmatrix}$$

(4)

When the moth reaches nearer to the moon then the moth starts to follow the spiral motion which can be specified by using eq.(5) as shown:

$$MP_{i,j} = FP_j + \left| FP_j - FM_i \right| * cos(2\pi t) * e^{bt}$$

(5)

The $MP_{i,i}$ denotes the updated position using the spiral motion while the b is a constant to define shape of the motion. The t is used to define the moth and flame relationship if the value of t is 1 then the moth follows the flame, resulting the best possible position near the flame is selected otherwise the moth selects the best far position from the flame. This updated position is used to move towards the optimization. The number of flames is decreasing with the increase in iteration which can be represented by eq. (6)

$$Count(F) = ceil\left(nm - itr_{no} * \frac{nm-1}{MAX_{itr}} \right)$$

(6)

Where the total number of iterations and the current iteration number is given by the MAX_{itr} and itr_{no} respectively

[1]. This process is used attain the global optima. The detail of dolphin has been described in next section.

III. DOLPHIN

Dolphins, similar to people, have expansive brains, live in obviously complex social gatherings, and speak with a broad collection of acoustic signs [11, 12]. Without a doubt, dolphins have a famous status in mainstream culture as a higher type of insight, yet how advanced and dialect like dolphin correspondence truly is, and how keen they are all in all, remain fervently. The logical contention goes back to the mid 1960s when John Lilly [13] recommended that dolphins trade keen data, utilize human-like conversational tenets to do as such, and even endeavor to set up between species correspondence with people. Albeit couple of researchers today would completely acknowledge such claims, later reviews recommend that, as with human dialect, social learning is fundamentally required in the improvement of dolphin correspondence [14], that dolphins can mimic each other's calls [15], and that, together with different cetaceans, they have socially transmitted lingos [16, 17]. These adaptable open capacities may support dolphins' clear limit with regards to complex types of social association, a thought upheld by another investigation of their mark shrieks [18]. Most types of dolphins create two sorts of sounds, which conceivably assume the part of correspondence flags in their social connections. These are packs of broadband heartbeats and "shrieks" [13]. Dolphins comprehend word arrange (language structure), word meaning (semantics) conceptual thought, and show mindfulness [13, 14]. These trials have been with regards to a restricted exhaustive circumstance. Indeed, even with these human imperatives, dolphins perform adroitly at adjusting to our correspondence framework. Beside people, dolphins have the most noteworthy encephalization remainder (EQ), a measure of cerebrum to body proportion [15]. Like primates, elephants, and a few types of flying creatures, dolphins have complex social structure, correspondence signs, and social legislative issues thought to be components for driving the development of focalized insight. Taking a gander at non-human creature social orders on earth may help us comprehend diverse sorts of insight and create models to associate with an outsider society outside our own particular planet. Dolphin brains are composed uniquely in contrast to human brains, however the exceedingly convoluted brains of numerous dolphins and different odontocetes are likewise altogether bigger than the human mind. The cerebrum to-body measure proportion is utilized for looking at and evaluating a creature's general knowledge or discernment. The encephalisation remainder (EQ) is an estimation of the relative mind measure, which is characterized as the proportion of the genuine to the anticipated cerebrum mass of a creature of a given size, and is ascertained utilizing the condition:

$$EQ = \frac{brain-weight}{(0.12*body-weight^{2}/_{3})}$$

(7)

EQ calculations consider allometric impacts, which detail that the skeleton turns out to be especially more hearty and enormous in connection to the extent of the body as the last increments.

It is conjectured that EQ gives a gauge of the knowledge level or discernment of a specific creature. The normal human cerebrum weighs around 1.3 kg, yet the bottlenose dolphin mind, averaging 1.7 kg, is around 25% heavier. The bigger brains of dolphins and whales may be because of their bigger bodies. Current people have the most astounding EQ: around 7, so our brains are around 7 times the size one would expect for a creature of our body estimate. Yet, numerous dolphins have EQs in the 4–5 territory, tantalizingly near the present day human level, and essentially higher than every other creature. Like people, dolphins are, unquestionably, brainiacs of the set of all animals. Due to such emanant properties dolphin can be mimicked for the optimization process discussed in next section.

IV. MOTH DOLPHIN OPTIMIZATION ALGORITHM

The previous section describes the dolphin and its various features. The Dolphins, similar to people, have expansive brains, live in obviously complex social gatherings, and speak with a broad collection of acoustic signs [17][18]. This paper embeds the communication behavior of the dolphin to the Moth, resulting. The moth follows the flames already described in the section 2 to travel towards the moon. Each moth follow different path based on its conditions. Here, Moth can communicate with each other and the best path as well as the worst path can be communicated among all Moth. This process leads to the position updation of the moth towards the best path to the moon. This can be denoted by the eq. (8)

$$P_j' = P_j + r_1 \left(P_{B_j} - |P_j| \right) - r_2 \left(P_{W_j} - |P_j| \right)$$

(8)

Here, the current position of the moth is updated which moves towards the best route position and avoids the worst route. This updated position is selected only if the corresponding fitness value is better than the existing fitness value. The detail procedure is shown in the form of algorithm given in next subsection.

Algorithm:
a) Initialize each Moth
 For i=1:n
  For j=1:Dimension
   $P_{i,j}$= random point within given region
  End
  F_i = Objective Function(P_i)
 End
b) [Flame_F index]=sort(F)
c) Flame=P(index)
d) Initiate Iteration say i=1
e) While $i \leq Max\_iter$
 F_{Pi} = Objective Function(P_i)

$$P_i = \bigvee_{j=1}^{Dimension} |Flame_j - P_i| * e^{bt} * cos(2\pi t) + Flame_j$$

$$P_{Best_i} = Flame(1)$$
$$P_{worst_i} = Flame(n)$$
$$P_i' = P_i + r_1 \left(P_{B_i} - |P_i| \right) - r_2 \left(P_{W_i} - |P_i| \right)$$
F_i'= Objective Function(P_i')
$P1_i$=QuickSort(P_i',P_i)
 $F1_i$= QuickSort(F_i',F_i)
 P=QuickSort($P1_i$,P_i)
 F= QuickSort($F1_i$,F_i)
 Update b and t
 Update number of flames
$$n = ceil\left(n - i * \frac{n-1}{Max\_iter} \right)$$
$i = i + 1$
 End while
f) Exit

The above algorithm follows the flame for the optimization along with the position updation based on worst and best position. This algorithm must converge towards the global optima due to use of exploration as well as exploitation search. The initialization process uses the exploration search. While the position updation uses the exploration as well as the exploitation along with the convergence. The performance analysis of the algorithm is done in next section.

V. PERFORMANCE EVALUATION

The performance of the MDOA is compared with the existing latest stable version of genetic algorithm [6], NSGA [8] and latest version of PSO [5], MPSO. The algorithm is also compared with basic version of DE due to its stability and the MFOA as it is one of the latest benchmark optimization technique. The comparison has been done on different unimodal and multimodal functions described in table 1 and table 2 respectively.

Table 1: Unimodal Benchmark Functions

Acronym	Function	Dim	Range	Value
F1	$f(a) = \sum_{b=1}^{n} ba_b^2$	100	[-100,100]	0
F2	$f(a) = \sum_{b=1}^{n} a_b^2$	100	[-100, 100]	0
F3	$f(a) = \sum_{b=1}^{n} ba_b^4 + random[0,1)$	100	[-100, 100]	0
F4	$f(a) = 100(a_1^2 - a_2)^2 + (a_1 - 1)^2$ $+ (a_3 - 1)^2 + 90(a_3^2 - a_4)^2$ $+ 10.1((a_2 - 1)^2 + (a_4 - 1)^2)$ $+ 19.8(a_2 - 1)(a_4 - 1)$	10	[-100, 100]	0
F5	$f(a) = \sum_{b=1}^{n-1} [100(a_{b+1} - a_b^2)^2 + (a_b - 1)^2]$	30	[-100, 100]	0
F6	$f(a) = \sum_{(b=1)}^{(n/k)} (a_{(4b-3)} + 10a_{(4b-2)})^2$ $+ 5(a_{(4b-1)} + a_{4b})^2 + (a_{(4b-2)} + a_{(4b-1)})^4$ $+ 10(a_{(4b-3)} + a_{4b})^4$	24	[-100, 100]	0
F7	$f(a) = -(a_1 - 1)^2 + \sum_{b=0}^{n} i(2a_b^2 - a_b - 1)^2$	10	[-100, 100]	0
F8	$f(a) = -cos(a_1)cos(a_2)$ $exp(-(a_1 - \pi)^2 - (a_2 - \pi)^2)$	10	[-100, 100]	-1

The table 1 describes the different separable as well as inseparable unimodal functions along with their dimension, range and the value. Each function has been assigned an acronym to used for notation in the rest paper.

Table 2: Multimodal Benchmark Functions

Acronym	Function	Dim	Range	Value
F9	$f(a) = \sum_{b=1}^{n} a_b^2 - 10\cos(2\pi a_b) + 10$	100	[-100, 100]	0
F10	$f(a) = \sum_{b=1}^{n} - a_b \sin\left(\sqrt{|a_b|}\right)$	100	[-500, 500]	0
F11	$f(a) = -\sum_{b=1}^{n} \sin(a_b)(\sin(ba_b^2 / \pi))^{2m}$	30	[0, π]	-4.688
F12	$f(a) = \left[\dfrac{1}{500} + \sum_{b=1}^{25} \dfrac{1}{b + \sum_{c=1}^{2}(a_c - d_{cb})^6}\right] - 1$	30	[-100, 100]	0.998
F13	$f(a) = -\sum_{b=1}^{5}[(a - c_b)(a - c_b)^T + d_b]^{-1}$	30	[0, 10]	-10.151
F14	$f(a) = \sum_{c=1}^{n}\sum_{b=1}^{n}(b^c + \beta)(a_i / b)^c - 1)^2$	30	[-D, D]	0
F15	$f(a) = \sum_{b=1}^{m}(X_b - Y_b)^2$	100	[-100, 100]	0
F16	$f(a) = -\sum_{b=1}^{m} p_b (exp(-1 / \sum_{(c=1)}^{n}(a_c - p_{bc})^2)$ $cos(\pi\sum_{(c=1)}^{n}(a_c - p_{bc})^2)))$	100	[0, 10]	0
F17	$f(a) = 0.5 + \dfrac{\sin^2(\sqrt{a_1^2 + a_2^2}) - 0.5}{\left(1 + 0.0001\left(\sqrt{a_1^2 + a_2^2}\right)\right)^2}$	10	[-100, 100]	0
F18	$f(a) = \dfrac{1}{4000}\sum_{b=1}^{n} a_b^2 - \prod_{b=1}^{n}\cos\dfrac{a_b}{\sqrt{b}} + 1$	100	[-600, 600]	0
F19	$f(a) = \sum_{b=1}^{11}(p_b - \dfrac{a_1(q_b^2 + q_b a_2)}{q_b^2 + q_b a_3 + a_4})^2$	10	[-100, 100]	0.00031
F20	$X_a = \sum_{b=1}^{n}(p_{ab}\sin\phi_b + q_{ab}\cos\phi_j)$ $Y_a = \sum_{b=1}^{n}(p_{ab}\sin\gamma_b + q_{ab}\cos\gamma_b)$ $f(p) = \sum_{a=1}^{m}(X_a - Y_a)^2$	10	[-100, 100]	0

Table 2 presents several multimodal functions. The description contains the dimension, range and value. Each function has been assigned an acronym to be used for notation in the rest paper. The comparison of mean and the standard deviation for the score obtained on the different benchmarks functions described in table 1 and table 2 are shown in the table 3 and table 4 respectively. The process is repeated for the 1000 iteration in each algorithm. The number of moths is 300 while all the other parameters are taken as used by corresponding authors.

Table 3: Performance Evaluation on Unimodal Functions

Function	MDOA	MFOA	NSGA [8,6]	MPSO[10, 5]	DE[7]
F1	2.798E-17	5.187E-12	2.480E-02	4.981E-07	0.001E-02
	±0.110E+00	±0.044E+00	±1.0041E+01	±0.010E+00	±0.010E+00
F2	0.010E-12	1.781E-09	1.0010E+03	0.010E+00	1.010E+03
	±0.004E+00	±3.171E+00	±2.421E+01	±0.0004E+00	±1.0001E+03
F3	0.757E-08	0.907E-04	1.807E+00	1.157E-03	0.3613E-03
	±6.780E-03	±8.911E-02	±2.711E-02	±1.760E-04	±4.170E-04
F4	0.078E-07	0.944E-03	1.494E-02	0.008E+00	4.091E-02
	±0.011E+00	±0.356E-00	±3.564E-03	±0.010E+00	±8.198E-02
F5	0.100E-12	1.870E-09	6.804E+00	1.100E-06	2.170E-07
	±0.140E-08	±1.660E-08	±0.548E+00	±0.040E-06	±1.360E-07
F6	3.748E-07	1.789E-02	1.960E+05	5.748E-01	1.685E+02
	±2.137E+00	±4.838E+00	±3.850E+06	±3.037E+01	±6.468E+01
F7	1.667E-08	1.237E-03	1.220E+03	6.667E-03	6.667E-03
	±0.010E+00	±0.110E+00	±2.660E+02	±0.000E+00	±0.000E+00
F8	-0.900E-12	−1.180E-07	−1.090E+00	−0.900E+00	−1.080E+00
	±0.080E+02	±0.100E+00	±0.300E+00	±0.080E+00	±0.000E+00

The score improvement in all the unimodal functions can be observed in the MDOA as compared to the other state of art techniques. The improvement converges towards the global optima.

Table 4: Performance Evaluation on Multimodal Functions

Function	MDOA	MFOA	NSGA [8,6]	MPSO[10, 5]	DE[7]
F9	-1.239E-12	-1.0266E-08	-1.159E-02	-6.909E-7	-1.0266E-04
	±1.875E-02	±2.208E-02	±3.325E+01	±6.790E+02	±3.208E+02
F10	1.373E-09	0.225E-05	4.292E-01	1.681E-01	0.172E-01
	±2.564E-03	±1.538E-01	±4.564E+00	±7.412E+00	±2.538E+00
F12	6.993E-10	1.034-03	9.890E-03	9.890E-03	9.890E-03
	±0.110E-02	±0.540E-01	±0.010E+00	±0.030E+00	±0.040E+00
F13	-1.652E-09	-0.315E-03	-3.661E-02	-1.087E-01	-0.715E-01
	±2.121E-03	±0.309E-02	±4.877E+00	±5.878E+00	±0.009E-08

F14	0.419E-09	3.786E-06	1.927E-04	3.605E-03	1.301E-03
	±0.478E-01	±2.137E-02	±1.933E-01	±4.893E-02	±4.603E-02
F15	0.100E-29	0.070E-12	0.110E-08	0.070E-05	0.110E-07
	±0.110E-02	±0.600E-01	±0.110E-09	±0.600E-08	±0.400E-04
F16	-2.694E-07	-1.423E-04	-7.694E-03	0.100E-08	-1.181E-03
	±1.101E-03	±1.812E-02	±1.865E-02	±0.010E+00	±1.551E-04
F17	1.139E-13	1.189E-09	2.139E-03	5.760E-03	0.010E+00
	±3.834E-03	±3.785E-03	±3.839E-03	±1.000E-02	±0.110E-01
F18	0.794E-09	0.183E-05	0.083E-01	9.877E-05	0.108E-03
	±1.161E-01	±2.291E-01	±0.161E+00	±1.158E-02	±8.470E-04
F19	1.927E-11	1.187E-05	3.827E-03	3.976E-04	3.176E-05
	±0.981E-05	±8.781E-05	±7.971E-05	±1.860E-04	±1.730E-05
F20	1.457E+03	4.303E-03	4.303E-03	1.457E-02	5.989E+00
	±1.269E+03	±9.469E-03	±9.469E-03	±1.269E-02	±7.334E+00

The performance on multimodal function of MDOA is better than the other existing state of art techniques shown in the table 4. This is due to the use of exploration and exploitation phenomena in the searching. The test function of the unimodal and multimodal along with their convergence curve are shown in figure 1 and figure 2 respectively.
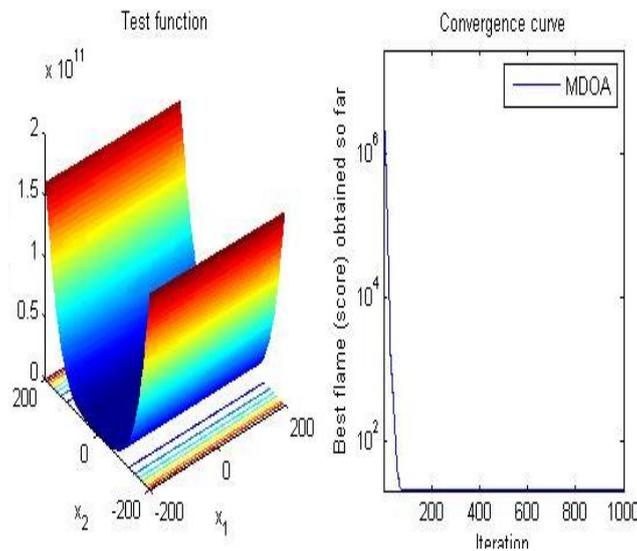

Figure 1. Unimodal Test Function and Convergence Curve of MDOA

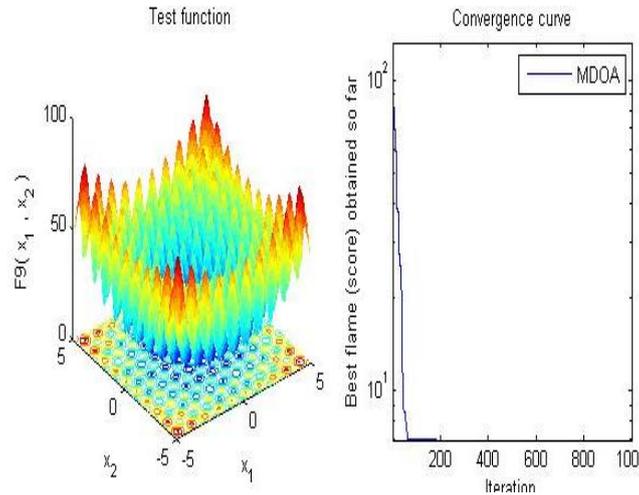# Moth-Dolphin Optimization Algorithm: A Nature Inspired Technique

Figure 2. Multimodal Test Function and Convergence Curve of MDOA

The convergence curve shown for multimodal and the unimodal function, converges in less than 100 and less than 200 iterations in the unimodal and multimodal functions respectively. The better performance of the proposed algorithm is better than other state of art techniques due to the use of exploration and exploitation search.

VI. CONCLUSION

This paper proposes a moth-dolphin based optimization algorithm. The proposed algorithm hybrid the routing behavior of moth and communication behavior of dolphin to achieve the global optima. The dolphin behavior enables moth to select the best path and to avoid the worst path i.e. to avoid the local optima and to achieve the global optima. The performance comparison of the algorithm is done latest stable version of the genetic algorithm, particle swarm optimization i.e. non dominated sorting genetic algorithm and modified particle swarm optimization. The algorithm is also compared with moth flame optimization and differential evolution over 20 unimodal and multimodal functions. The better performance of the algorithm as compared to existing state of art techniques proves significance of the algorithm. In future, MDOA can be applied in various application areas including routing, feature selection etc.

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