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Literature Review of Harris Hawk Optimization Algorithm

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ABSTRACT

The Harris Hawks Optimizer is a revolutionary population-based, nature-inspired optimization methodology proposed in this paper (HHO). The cooperative behaviour and pursuit manner of Harris' hawks in nature, known as surprise pounce, is the fundamental inspiration for HHO. Several hawks work together to pounce on a victim from different directions in an attempt to catch it off guard. Based on the dynamic nature of events and the prey's escape behaviours, Harris hawks can display a range of pursuit patterns. To design an optimization algorithm, this work mathematically duplicates such dynamic patterns and behaviours. On 29 benchmark problems and numerous real-world engineering challenges, the effectiveness of the proposed HHO optimizer is tested by comparing it to other nature-inspired approaches. The statistical results and comparisons show that the HHO algorithm provides very promising and occasionally competitive results compared to well established metaheuristic techniques. When compared to well-established metaheuristic techniques, the statistical results and comparisons reveal that the HHO algorithm delivers highly promising and occasionally competitive outcomes.

Keywords: Swarm intelligence, Optimization, Metaheuristic, Harris hawks optimization method, Nature-inspired computing.

INTRODUCTION

Many real-world problems in machine learning and artificial intelligence have generally a continuous, discrete, constrained or unconstrained nature [1, 2].

Some kinds of problems are difficult to solve using traditional mathematical programming methodologies 4 including conjugate gradient, sequential quadratic programming, rapid steepest, and quasi-Newton 5 methods [3, 4].

Several studies have shown that these strategies are not always or even seldom effective in dealing with many large-scale real-world multimodal, non-continuous, and 7 non-differentiable situations [5].

BACKGROUND

Heidari and Mirjalili et al. created the Harris Hawks Optimization Algorithm (HHO) in 2019 [35]. The programme mimics the natural behaviour and hunting strategy of Harris Hawks known as surprise pounce. The Hawks attack from multiple directions to surprise the prey in this clever approach. Harris Hawks reveals a variety of pursue methods based on the nature of the schemes and the victim's evasive patterns. Investigation and exploitation tactics are proposed by the conventional HHO algorithm, which are prompted by prey exploration, surprise pounce, and Harris Hawks' distinctive attacking technique. Algorithm HHO The HHO algorithm is a slope optimization and population-based approach. As a result, it has been applied to a variety of optimization issues that have been properly formulated. The HHO then develops an optimization method by mathematically simulating these useful strategies and behaviours.

EXPLORATION PHASE

All Harris hawks are considered candidate solutions during this phase. The fitness value is determined for all of these feasible solutions based on the desired prey in each iteration. Two techniques are used to simulate Harris Hawk exploration performance in the search space defined in (1) X(t + 1) = { Xrand(t) − r1 |Xrand(t) − 2r2X(t)| q ≥ 0.5 (Xrabbit(t) − Xm(t)) – r3(LB + r4(UB − LB)) q < 0.5 where X (t + 1) is the Hawks' position in iteration 2.The prey position is Xrabbit (t), and the random solution chosen in the current population is Xrand (t). X (t) is the Hawks' current position vector, r1,r2,r3,r4, and q are random scaled factors inside [0, 1], which are updated in each iteration, LB and UB are the variables' upper and lower bounds, and Xm is the average number of solutions. The placements of Hawks within (UB LB) boundaries are generated using two rules: 1) construct the solutions using a randomly selected hawk from the present population and the other hawks. 2) Create solutions based on the location of the prey, the average Hawk position, and random scaled factors. While r3 is a scaling factor, if the value of r4 approaches 1, it will aid in increasing the rule's randomness. A arbitrarily scaled movement length is added to LB in this rule. More diversification strategies to investigate other sections of the feature space are considered with a random scaled component. The average hawk stance (solutions) is formulated as follows: (2). Xm (t) = 1 N X N i=1 Xi (t) The average number of solutions in the current iteration is Xm (t). N stands for all conceivable outcomes. The location of each solution in iteration t is indicated by Xi (t), which was generated using chaos theory. When the hawk uses the knowledge from the random hawks to grab the prey, rule one is usually used in

Eq. (1). The second rule is used when all hawks agree on the best option and the best hawk is used.

TRANSITION FROM EXPLORATION TO EXPLOITATION

Based on the energy of the prey, this phase shows how HHO moves from exploration to exploitation (E). HHO posits that prey energy is gradually depleted as a result of fleeing efforts. E0 is the initial energy drop modelled in [1, 1]. (3). E = 2E0 1 − t T , E0 ∈ [−1, 1] T is the maximum number of iterations, while t represents the current iteration.

EXPLOITATION PHASE

The exploitation phase is completed utilising four ways at parameter sets in this phase. These methods are based on the position that was discovered during the exploration phase. However, the prey attempts to flee constantly, despite the hawks' efforts to track it down and trap it. HHO exploitation uses four different techniques to imitate the Hawks' assault strategy.

Soft besiege, hard besiege, soft besiege with progressive rapid dives, and hard besiege with progressive rapid dives are the four approaches. These methods are based on two variables, r and |E|, which describe the method to be used. Where |E| is the prey's fleeing energy and r is the likelihood of escaping, with r< 0.5 indicating a higher chance of the prey escaping successfully and r >=0.5 indicating an unsuccessful escape. The following is a summary of these approaches: The rabbit still has some energy to escape in the soft besiege method, where r >=0.5 and |E|>= 0.5, and the hawks are softly encircling the prey, causing it to lose more energy before completing the surprise pounce. In (4), (5), and (6), soft besiege is mathematically formulated

Strategies of Harris Hawk optimization

Besiege softly:

The following rules are used to model this behaviour:

$$X(t + 1) = \Delta X(t) - E\ |J X_{rabbit}(t) - X(t)| \qquad (4)$$

$$\Delta X(t) = X_{rabbit}(t) - X(t) \qquad (5)$$

where X(t) represents the difference between the rabbit's position vector and the iteration's current location.

t, r5 is a random value within (0,1), and J = 2(1-r5) is the rabbit's random jump strength.

Throughout the process of eluding capture. To simulate nature, the J value changes at random in each iteration.motions of a rabbit. This process can happen when not successfully escaping chance r is

r>=0.5 and the escaping energy of the prey E equals E>=0.5

Hard besiege:

If the prey has a small amount of escaping energy |E|<0.5 and grows exhausted while attempting to escape r>=0.5 The Harris hawks surround the target and attack unexpectedly.
In this situation, the current positions are updated using

Eq. X(t + 1) = Xrabbit(t) − E |ΔX(t)| (6)

Soft besiege with progressive rapid dives:

If the prey has enough energy to escape |E|>=0.5, it can successfully escape r<0.5. In this case, the Harris hawks apply a smooth besiege to attack the prey. To perform a soft besiege, we supposed that the hawks can evaluate (decide) their next move based on the following Eq. Y = Xrabbit(t) − E |JXrabbit(t) − X(t)| (7) The zig-zag motion of the prey during the escaping process can be simulated by using Levy flight (LF) operator. We supposed that they will dive based on the LF-based patterns) using the following rule: Z = Y + S × LF(D). (8)

Where D is the problem dimension, S is a random vector of size 1×D, and LF is the levy flight function derived using Eq.: $LF(x) = 0.01 \times \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}}, \sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}}\right)^{\frac{1}{\beta}}$ (9)

where u, v are random values inside (0,1), β is a default constant set to 1.5.

As a result, Eq. $X(t+1) = \begin{cases} Y & \text{if } F(Y) < F(X(t)) \\ Z & \text{if } F(Z) < F(X(t)) \end{cases}$ (10)

may conduct the final strategy for updating the positions of hawks in the soft besiege phase. Only the better place Y or Z will be chosen as the next location in each phase.
This approach is used by all search agents.

Hard besiege with progressive rapid dives:

When |E| <0.5 and r < 0.5, the rabbit lacks the energy to flee, and a hard besiege is built before the surprise pounce to catch and kill the victim. On the prey side, the scenario is identical to that of the soft besiege, but this time, the hawks try to decrease the distance of their average location with the escaping prey. Therefore, the following rule is performed in hard besiege condition: $X(t+1) = \begin{cases} Y & \text{if } F(Y) < F(X(t)) \\ Z & \text{if } F(Z) < F(X(t)) \end{cases}$ (11)

where Y and Z are $Y = X_{\text{rabbit}}(t) - E|JX_{\text{rabbit}}(t) - X_m(t)|$ (12)

$Z = Y + S \times LF(D)$ (13)

Pseudocode of Harris Hawks Optimization:

Inputs: N and I
Outputs: prey location and its fitness value
Initialize (Xi,i=1,2,3,4…,N)
while (stopping condition is not met) do
Calculate the fitness values of hawks
Set X_"prey " as the location of prey (best location)
for (each hawk (Xi)) do
Update the initial energy E_0 and jump strength J
E_0=2rand(0-1)," " J=2(1-rand 0)
Update the E using Eq. (3)
if (|E|≥1) then
Update the location vector using Eq. (1) if (|E|<1) then
if (r≥0.5 and |E|≥0.5) then
Update the location vector using Eq. (4)
else if (r≥0.5 and |E|<0.5) then
Update the location vector using Eq. (6)
else if (r<0.5 and |E|≥0.5) then
with progressive rapid dives
Update the location vector using Eq. (10)
else if (r<0.5 and |E|<0.5) then
with progressive rapid dives
Update the location vector using Eq. (11)
Return X_"prey "

Application Domains of Harris Hawk optimization

HHO was utilised in three primary domains (engineering, computer-science, and medicine and public health). 49 HHO-related research in total were used to address a variety of engineering optimization issues. Seven HHO-related research were undertaken in the field of
computer science to identify answers to issues with picture thresholding optimization, such as multilayer image segmentation and enhanced thresholding function parameters.

Additionally,

five HHO-related studies were used to optimise issues with networking and distributed systems, including the problems of web service composition, distribution network
reconfiguration, the deployment of large-scale wireless sensor networks, complex combinatorial optimization, and visible-light communications. To improve data mining and
data processing issues such job scheduling, data clustering, and feature selection, four HHO-related research was nonetheless introduced. Last but not least, two research employed HHO to improve various software engineering issues

including the cost of regression testing and foreseeing problematic components in software projects. HHO was also used in the fields of medicine and public health. It was used to solve the chemical descriptor selection challenge in drug design. Additionally, one study used HHO to address the feature selection issue for breast mass classification.

Conclusion

The HHO is a relatively new method that has drawn the attention of many scholars for its ability to address several sorts of optimization problems, such as modification, hybridization,
multi objective, binarization, and chaotic.

Several improved versions of HHO have been compiled, reviewed, and analyzed, where the proposed versions of HHO support to improve the performance of the original HHO. Several
improved versions of HHO have been compiled, reviewed, and analyzed, where the proposed versions of HHO support to improve the performance of the original HHO.
The performance of the original HHO has been enhanced by a number of upgraded versions of HHO that have been assembled, evaluated, and studied. The methods used to validate the efficacy and performances of HHO (benchmark functions/performance measures and comparison algorithms) were discovered. The evaluation results demonstrate that HHO is strongly viable for continued employment in the community due to a number of features provided by this algorithm, including (1) ease of use, usefulness, and flexibility of HHO, (2) high quality exploration and exploitation results to find a solution for the decision variables under different optimization situations, and (3) effectiveness of HHO and/or HHO versions to handle various types of optimization problems, variables, fitness function, and more. There may be several HHO variants that seem to be appropriate for the specific optimization challenge. Therefore, choosing the best optimizer from among the several HHO versions is a difficult process. Therefore, a suggested avenue for future research is an experimental study to assess and compare various HHO versions across a range of optimization issues. Such a study may attempt to: (1) explain which version of HHO is better suited for each type of optimization problem under consideration; (2) explain the benefits and drawbacks of applying one version over another; (3) explain whether the optimization solution alters when applying different versions; and (4) pinpoint the variables influencing the performance of HHO versions.

References

1. Heidari AA, Mirjalili S, Faris H, Aljarah I, Mafarja M, Chen H(2019) Harris hawks

2. optimization: algorithm and applications.Future Gener Comput Syst 97:849–872

3. Hussien, A.G.; Abualigah,L.; Abu Zitar, R.; Hashim, F.A.; Amin,M.; Saber, A.; Almotairi, K.H.;Gandomi, A.H. Recent Advances inHarris Hawks Optimization:A Comparative Study andApplications. Electronics 2022,11 1919.