https://aliasgharheidari.com/HHO.html

A brief description of the HHO algorithm

1. Harris hawks optimization (HHO)

Figure 1 shows all phases of HHO, which are described in the next subsections.

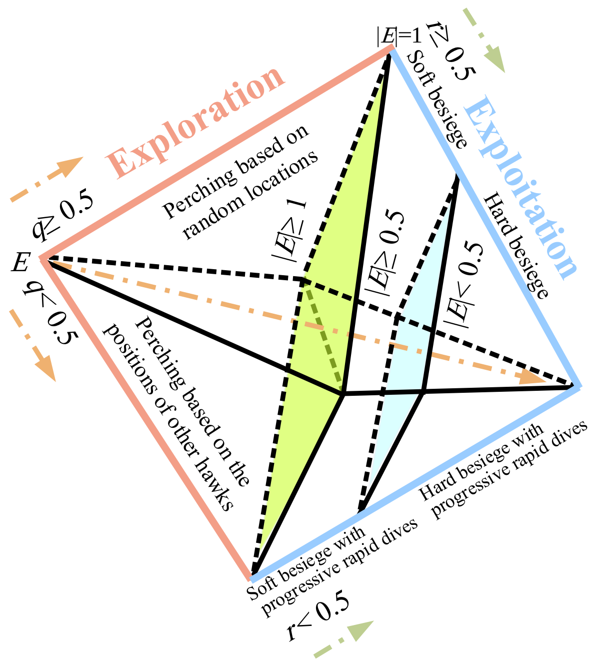


Figure 1: Different phases of HHO

1.1. Exploration phase

In HHO, the Harris' hawks perch randomly on some locations and wait to detect a prey based on two strategies.

$$X(t+1) = \begin{cases} X_{rand}(t) - r_1 \left| X_{rand}(t) - 2r_2 X(t) \right| & q \geq 0.5 \\ (X_{rabbit}(t) - X_m(t)) - r_3(LB + r_4(UB - LB)) & q < 0.5 \end{cases} \quad (1)$$

where $X(t+1)$ is the position vector of hawks in the next iteration t, $X_{rabbit}(t)$ is the position of rabbit, $X(t)$ is the current position vector of hawks, r_1, r_2, r_3, r_4, and q are random numbers inside (0,1), which are updated in each iteration, LB and UB show the upper and lower bounds of variables, $X_{rand}(t)$ is a randomly selected hawk from the current population, and X_m is the average position of the current population of hawks. The average position of hawks is attained using Eq. (2):

$$X_m(t) = \frac{1}{N} \sum_{i=1}^{N} X_i(t) \quad (2)$$

where $X_i(t)$ indicates the location of each hawk in iteration t and N denotes the total number of hawks.

1.2. Transition from exploration to exploitation

To model this step, the energy of a rabbit is modeled as:

$$E = 2E_0(1 - \frac{t}{T}) \quad (3)$$

where E indicates the escaping energy of the prey, T is the maximum number of iterations, and E_0 is the initial state of its energy. The time-dependent behavior of E is also demonstrated in Fig. 2.

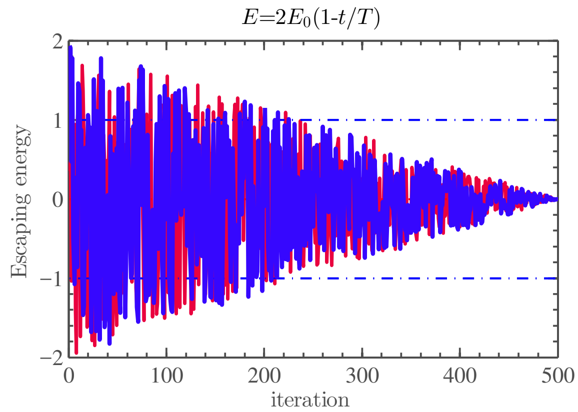


Figure 2: Behavior of E during two runs and 500 iterations

1.3. Exploitation phase

1.3.1. Soft besiege

This behavior is modeled by the following rules:

$$X(t+1) = \Delta X(t) - E\left|JX_{rabbit}(t) - X(t)\right| \tag{4}$$

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

where $\Delta X(t)$ is the difference between the position vector of the rabbit and the current location in iteration t, r_5 is a random number inside (0,1), and $J = 2(1 - r_5)$ represents the random jump strength of the rabbit throughout the escaping procedure. The J value changes randomly in each iteration to simulate the nature of rabbit motions.

1.3.2. Hard besiege

In this situation, the current positions are updated using Eq. (6):

$$X(t+1) = X_{rabbit}(t) - E\left|\Delta X(t)\right| \tag{6}$$

A simple example of this step with one hawk is depicted in Fig. 3.

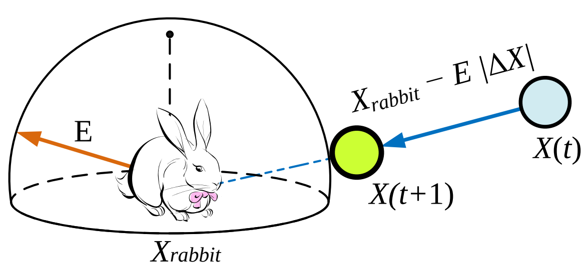


Figure 3: Example of overall vectors in the case of hard besiege

1.3.3. Soft besiege with progressive rapid dives

To perform a soft besiege, we supposed that the hawks can evaluate (decide) their next move based on the following rule in Eq. (7):

$$Y = X_{rabbit}(t) - E\left|JX_{rabbit}(t) - X(t)\right| \tag{7}$$

We supposed that they will dive based on the LF-based patterns using the following rule:

$$Z = Y + S \times LF(D) \tag{8}$$

where D is the dimension of problem and S is a random vector by size $1 \times D$ and LF is the levy flight function, which is calculated using Eq. (9):

$$LF(x) = 0.01 \times \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}}, \sigma = \left(\frac{\Gamma(1+\beta) \times sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2}) \times \beta \times 2^{(\frac{\beta-1}{2})})} \right)^{\frac{1}{\beta}} \tag{9}$$

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

Hence, the final strategy for updating the positions of hawks in the soft besiege phase can be performed by Eq. (10):

$$X(t+1) = \begin{cases} Y & if F(Y) < F(X(t)) \\ Z & if F(Z) < F(X(t)) \end{cases} \tag{10}$$

where Y and Z are obtained using Eqs.(7) and (8).

A simple illustration of this step for one hawk is demonstrated in Fig. 4.

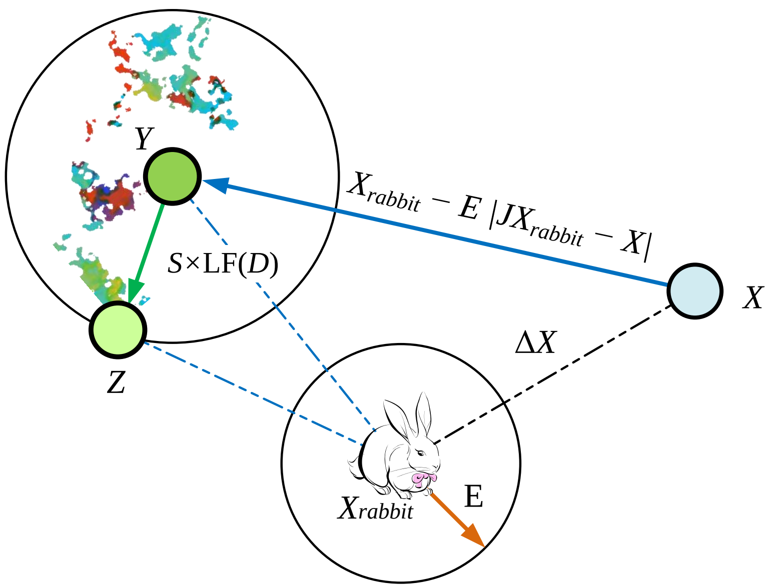


Figure 4: Example of overall vectors in the case of soft besiege with progressive rapid dives

1.3.4. Hard besiege with progressive rapid dives

The following rule is performed in hard besiege condition:

$$X(t+1) = \begin{cases} Y & if F(Y) < F(X(t)) \\ Z & if F(Z) < F(X(t)) \end{cases} \tag{11}$$

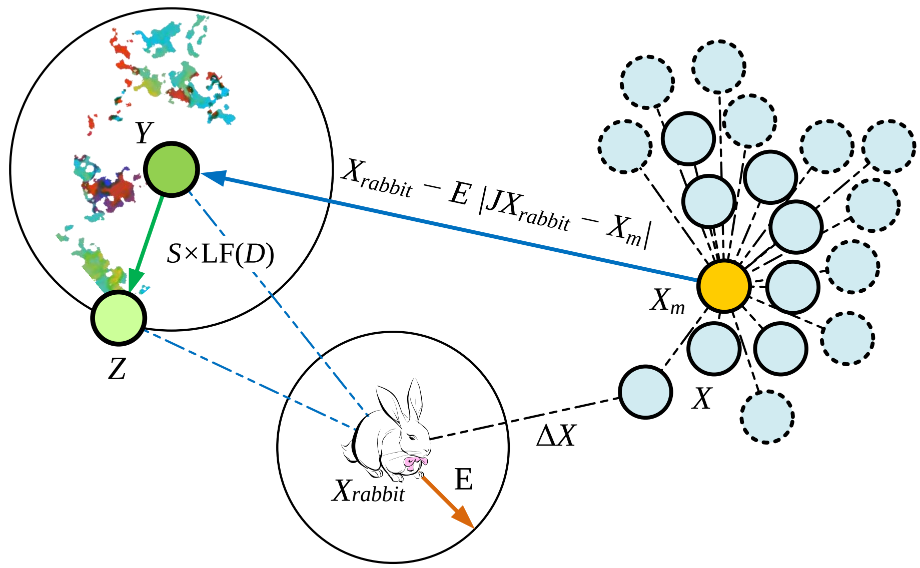
where Y and Z are obtained using new rules in Eqs.(12) and (13).

$$Y = X_{rabbit}(t) - E\,|JX_{rabbit}(t) - X_m(t)| \tag{12}$$

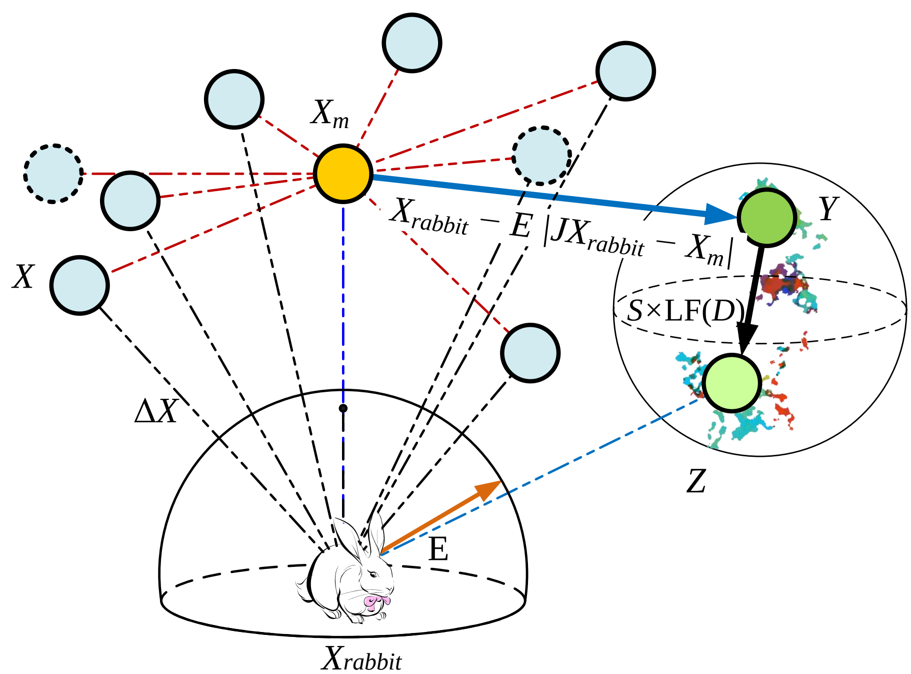
$$Z = Y + S \times LF(D) \tag{13}$$

where $X_m(t)$ is obtained using Eq. (2).

A simple example of this step is demonstrated in Fig. 5.



(a) The process in 2D space



(b) The process in 3D space

Figure 5: Example of overall vectors in the case of hard besiege with progressive rapid dives in 2D and 3D space.

1.4. Pseudocode of HHO

The pseudocode of the proposed HHO algorithm is reported in Algorithm 1.

Algorithm 1 Pseudo-code of HHO algorithm

```
Inputs: The population size N and maximum number of iterations T
Outputs: The location of rabbit and its fitness value
Initialize the random population X_i (i = 1, 2, ..., N)
while (stopping condition is not met) do
    Calculate the fitness values of hawks
    Set X_rabbit as the location of rabbit (best location)
    for (each hawk (X_i)) do
        Update the initial energy E_0 and jump strength J        ▷ E_0=2rand()-1, J=2(1-rand())
        Update the E using Eq. (3)
        if (|E| ≥ 1) then                                        ▷ Exploration phase
            Update the location vector using Eq. (1)
        if (|E| < 1) then                                        ▷ Exploitation phase
            if (r ≥0.5 and |E| ≥ 0.5 ) then                      ▷ Soft besiege
                Update the location vector using Eq. (4)
            else if (r ≥0.5 and |E| < 0.5 ) then                 ▷ Hard besiege
                Update the location vector using Eq. (6)
            else if (r <0.5 and |E| ≥ 0.5 ) then                 ▷ Soft besiege with progressive rapid dives
                Update the location vector using Eq. (10)
            else if (r <0.5 and |E| < 0.5 ) then                 ▷ Hard besiege with progressive rapid dives
                Update the location vector using Eq. (11)
Return X_rabbit
```

References

Harris Hawks Optimization: Algorithm and Applications, Ali Asghar Heidari and Seyedali Mirjalili and Hossam Faris and Ibrahim Aljarah and Majdi Mafarja and Huiling Chen, Future Generation Computer Systems, 2019.