An Artificial Human Optimization Algorithm titled Human Thinking Particle Swarm Optimization

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Note

This article is accepted for publication in another journal. This article is submitted for re-publication in this journal in an attempt to popularize “Artificial Human Optimization” Field like never before. The First Author of this paper (Satish Gajawada) is completely responsible for this action of re-publication.

Abstract

Artificial Human Optimization is a latest field proposed in December 2016. Just like artificial Chromosomes are agents for Genetic Algorithms, similarly artificial Humans are agents for Artificial Human Optimization Algorithms. Particle Swarm Optimization is very popular algorithm for solving complex optimization problems in various domains. In this paper, Human Thinking Particle Swarm Optimization (HTPSO) is proposed by applying the concept of thinking of Humans into Particle Swarm Optimization. The proposed HTPSO algorithm is tested by applying it on various benchmark functions. Results obtained by HTPSO algorithm are compared with Particle Swarm Optimization algorithm.

Indexing terms/Keywords:

Artificial Humans, Global Optimization Techniques, Artificial Human Optimization, Particle Swarm Optimization, Evolutionary Computing, Nature Inspired Computing, Genetic Algorithms, Bio-Inspired Computing

Introduction

More than 30 papers are published in Artificial Human Optimization Field. All optimization algorithms proposed based on Human Cognition, Human Behavior, Human Psychology and Human Thinking etc. will come under Artificial Human Optimization Field. Papers [1] - [8] give introduction to Artificial Human Optimization Field. Papers [9] - [13] are Particle Swarm Optimization Algorithms which come under Artificial Human Optimization Field.

Section 2 explains Particle Swarm Optimization Algorithm. The proposed Human Thinking Particle Swarm Optimization (HTPSO) is described in Section 3. Section 4 shows results obtained. The conclusion is given in Section 5.

2. Particle Swarm Optimization (PSO)

In PSO, first we initialize all particles as shown below. Two variables $pbest_i$ and gbest are maintained. $pbest_i$ is the best fitness value achieved by i^{th} particle so far and gbest is the best fitness value achieved by all particles so far. Lines 4 to 11 in the below text helps in maintaining particle best and global best. Then the velocity is updated by rule shown in line no. 14. Line 15 updates position of i^{th} particle. Line 19 increments the number of iterations and then the control goes back to line 4. This process of a particle moving towards its local best and also moving towards global best of particles is continued until termination criteria will be reached.

Procedure: Particle Swarm Optimization (PSO)

1) Initialize all particles

2) iterations = 0

3) **do**

4) **for** each particle i **do**

5) **If** (f(x_i) < f($pbest_i$)) **then**

6) $pbest_i = x_i$

7) **end if**

8) **if** (f($pbest_i$) < f(gbest)) **then**

9) $gbest = pbest_i$

10) **end if**

11) **end for**

12) **for** each particle i **do**

13) **for** each dimension d **do**

14) $v_{i,d} = v_{i,d} + C_1*Random(0,1)*(pbest_{i,d} – x_{i,d}) + C_2*Random(0,1)*(gbest_d – x_{i,d})$

15) $x_{i,d} = x_{i,d} + v_{i,d}$

17) **end for**

18) **end for**

19) iterations = iterations + 1

20) **while** (termination condition is false)

3. Human Thinking Particle Swarm Optimization (HTPSO)

Almost all Particle Swarm Optimization (PSO) algorithms are proposed such that the particles move towards best particles. But Human Thinking is such that they not only move towards best but also moves away from the worst. This concept was used to design algorithm titled “Multiple Strategy Human Optimization (MSHO)” in [4]. In MSHO, artificial Humans move towards the best in even generations and move away from the worst in odd generations. But in Human Thinking Particle Swarm Optimization, both strategies happen in the same generation and all generations follow the same strategy. That is moving towards the best and moving away from the worst strategies happen simultaneously in the same generation unlike MSHO designed in [4]. The Proposed HTPSO algorithm is shown below:

Procedure: Human Thinking Particle Swarm Optimization (HTPSO)

```
Initialize all particles
iterations = 0
do
    for each particle i do
        If ( f( x_i ) < f( pbest_i ) ) then
            pbest_i = x_i
        end if
        if ( f( pbest_i ) < f( gbest ) ) then
            gbest = pbest_i
        end if
        If ( f( x_i ) > f( pworst_i ) ) then
            pworst_i = x_i
        end if
        if ( f( pworst_i ) > f( gworst ) ) then
            gworst = pworst_i
        end if
    end for
    for each particle i do
        for each dimension d do
            v_i,d = w*v_i,d + Random(0,1)*(pbest_i,d – x_i,d) + Random(0,1)*(gbest_d – x_i,d)
            v_i,d = v_i,d + Random(0,1)*( x_i,d - pworst_i,d ) + Random(0,1)*( x_i,d - gworst_d)
            x_i,d = x_i,d + v_i,d
        end for
    end for
    iterations = iterations + 1
```

26) **while** (termination condition is false)

4. Results

This section shows results obtained after applying proposed HTPSO on various benchmark functions. The obtained results are compared with PSO algorithm. The figures and equations of benchmark functions are taken from [14].

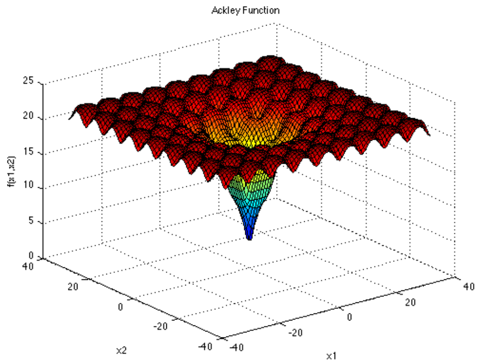


Figure 1 Ackley Function

$$f(\mathbf{x}) = -a \exp\left(-b\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - \exp\left(\frac{1}{d}\sum_{i=1}^{d}\cos(cx_i)\right) + a + \exp(1)$$

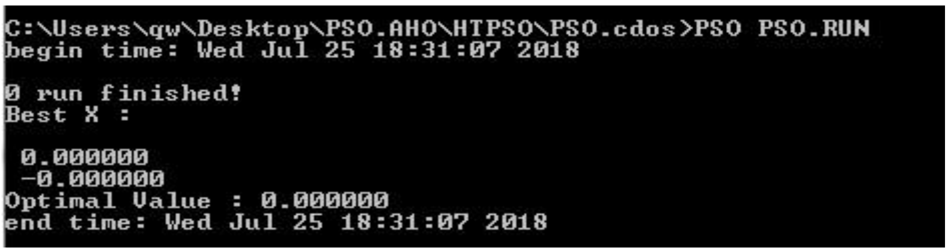
Figure 2 Equation of Ackley Function

```
C:\Users\qw\Desktop\PSO.AHO\HTPSO\HTPSO.cdos.pso.modified>pso pso.run
begin time: Wed Jul 25 16:19:22 2018

0 run finished!
Best X :

 0.429100
 -0.591114
Optimal Value : 4.262748
end time: Wed Jul 25 16:19:22 2018
```

Figure 3 Result given by HTPSO on Ackley Function



```
C:\Users\qw\Desktop\PSO.AHO\HTPSO\PSO.cdos>PSO PSO.RUN
begin time: Wed Jul 25 18:31:07 2018

0 run finished!
Best X :

 0.000000
 -0.000000
Optimal Value : 0.000000
end time: Wed Jul 25 18:31:07 2018
```

Figure 4 Result given by PSO on Ackley Function

From Figure 3 and Figure 4 we can see that Optimal value given by proposed HTPSO is 4.262748 where as PSO gave optimal solution as 0 which is the global optimal of Ackley Function. Hence PSO performed better than proposed HTPSO on Ackley Function.

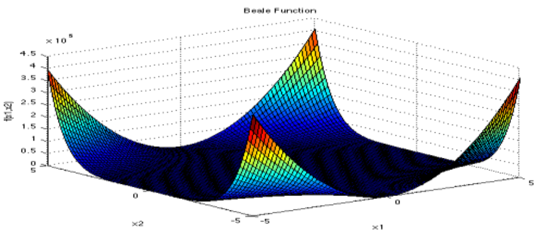


Figure 5 Beale Function

$$f(\mathbf{x}) = (1.5 - x_1 + x_1x_2)^2 + (2.25 - x_1 + x_1x_2^2)^2 + (2.625 - x_1 + x_1x_2^3)^2$$

Figure 6 Equation of Beale Function

```
C:\Users\qw\Desktop\PSO.AHO\HTPSO\HTPSO.cdos.pso.modified>PSO PSO.RUN
begin time: Wed Jul 25 17:52:43 2018

0 run finished!
Best X :

 2.729012
 0.332734
Optimal Value : 0.134325
end time: Wed Jul 25 17:52:43 2018
```

Figure 7 Result given by HTPSO on Beale Function

```
C:\Users\qw\Desktop\PSO.AHO\HTPSO\PSO.cdos>PSO PSO.RUN
begin time: Wed Jul 25 18:34:03 2018

0 run finished!
Best X :

 3.000000
 0.500000
Optimal Value : 0.000000
end time: Wed Jul 25 18:34:03 2018
```

Figure 8 Result given by PSO on Beale Function

From Figure 7 and Figure 8 we can see that Optimal value given by proposed HTPSO is 0.134325 where as PSO gave optimal solution as 0 which is the global optimal of Beale Function. Hence PSO performed better than proposed HTPSO on Beale Function.

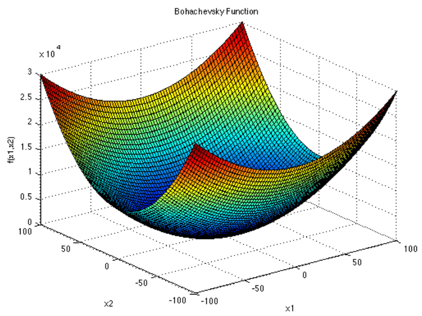


Figure 9 Bohachevsky Function

$$f_1(\mathbf{x}) = x_1^2 + 2x_2^2 - 0.3\cos(3\pi x_1) - 0.4\cos(4\pi x_2) + 0.7$$

Figure 10 Equation of Bohachevsky Function

```
C:\Users\qw\Desktop\PSO.AHO\HTPSO\HTPSO.cdos.pso.modified>PSO PSO.RUN
begin time: Wed Jul 25 17:11:18 2018

0 run finished!
Best X :

 -1.322266
 1.193764
Optimal Value : 5.305778
end time: Wed Jul 25 17:11:18 2018
```

Figure 11 Result given by HTPSO on Bohachevsky Function

```
C:\Users\qw\Desktop\PSO.AHO\HTPSO\PSO.cdos>PSO PSO.RUN
begin time: Wed Jul 25 18:37:40 2018

0 run finished!
Best X :

 -0.000014
 0.000002
Optimal Value : -0.000000
end time: Wed Jul 25 18:37:40 2018
```

Figure 12 Result given by PSO on Bohachevsky Function

From Figure 11 and Figure 12 we can see that Optimal value given by proposed HTPSO is 5.305778 where as PSO gave optimal solution as 0 which is the global optimal of Bohachevsky Function. Hence PSO performed better than proposed HTPSO on Bohachevsky Function.

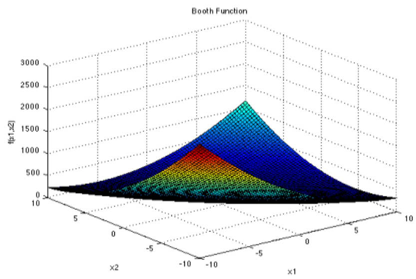


Figure 13 Booth Function

$$f(\mathbf{x}) = (x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2$$

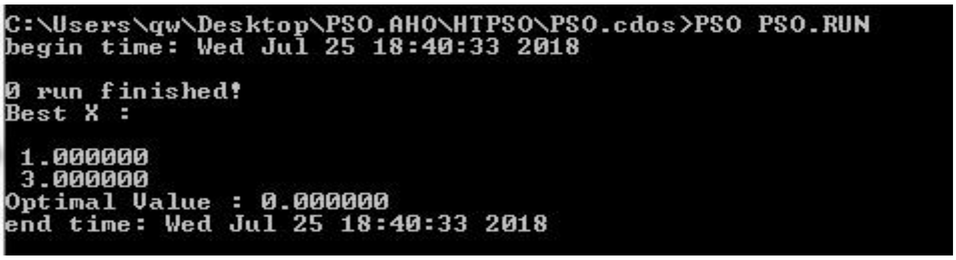
Figure 14 Equation of Booth Function


```
C:\Users\qw\Desktop\PSO.AHO\HTPSO\HTPSO.cdos.pso.modified>PSO PSO.RUN
begin time: Wed Jul 25 17:22:55 2018

0 run finished!
Best X :

 1.274603
 2.578953
Optimal Value : 0.338471
end time: Wed Jul 25 17:22:56 2018
```

Figure 15 Result given by HTPSO on Booth Function


```
C:\Users\qw\Desktop\PSO.AHO\HTPSO\PSO.cdos>PSO PSO.RUN
begin time: Wed Jul 25 18:40:33 2018

0 run finished!
Best X :

 1.000000
 3.000000
Optimal Value : 0.000000
end time: Wed Jul 25 18:40:33 2018
```

Figure 16 Result given by PSO on Booth Function

From Figure 15 and Figure 16 we can see that Optimal value given by proposed HTPSO is 0.338471 where as PSO gave optimal solution as 0 which is the global optimal of Booth Function. Hence PSO performed better than proposed HTPSO on Booth Function.

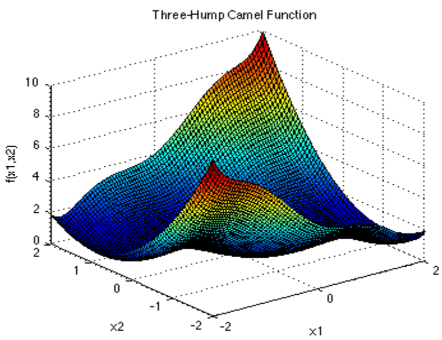


Figure 17 Three-Hump Camel Function

$$f(\mathbf{x}) = 2x_1^2 - 1.05x_1^4 + \frac{x_1^6}{6} + x_1x_2 + x_2^2$$

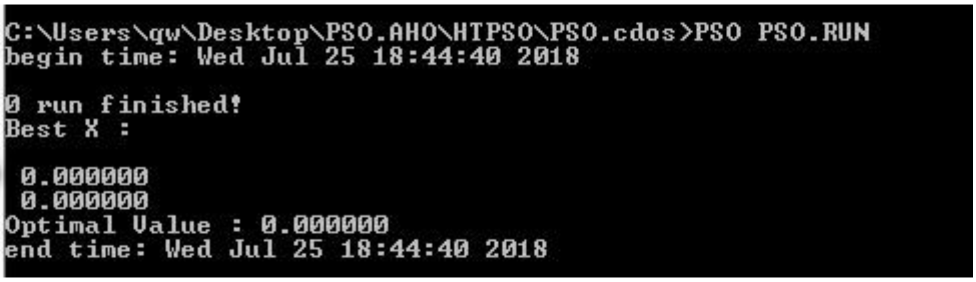
Figure 18 Equation of Three-Hump Camel Function

```
C:\Users\qw\Desktop\PSO.AHO\HTPSO\HTPSO.cdos.pso.modified>PSO PSO.RUN
begin time: Wed Jul 25 17:36:55 2018

0 run finished!
Best X :

 -0.069427
 -0.093796
Optimal Value : 0.024926
end time: Wed Jul 25 17:36:55 2018
```

Figure 19 Result given by HTPSO on Three-Hump Camel Function



```
C:\Users\qw\Desktop\PSO.AHO\HTPSO\PSO.cdos>PSO PSO.RUN
begin time: Wed Jul 25 18:44:40 2018

0 run finished!
Best X :

 0.000000
 0.000000
Optimal Value : 0.000000
end time: Wed Jul 25 18:44:40 2018
```

Figure 20 Result given by PSO on Three-Hump Camel Function

From Figure 19 and Figure 20 we can see that Optimal value given by proposed HTPSO is 0.024926. PSO gave optimal solution as 0 which is the global optimal of Three-Hump Camel Function. Hence both PSO and HTPSO performed well when applied on Three-Hump Camel Function.

5. Conclusion

An innovative algorithm titled "Human Thinking Particle Swarm Optimization (HTPSO)" is proposed in this paper. Results show that HTPSO and PSO both performed well on Three-Hump Camel Function. PSO performed better than HTPSO on all other benchmark functions. Overall PSO performed better than Human Thinking Particle Swarm Optimization (HTPSO) algorithm. This is just the beginning of research in Artificial Human Optimization Field. General Expectation is that algorithms based on Humans will perform better than other algorithms. In this paper it has been found that Artificial Human Optimization Algorithms might not always perform well. Based on this single paper we cannot say PSO is better than Artificial Human Optimization Algorithms. Still lot of work has to be done in this latest field titled "Artificial Human Optimization".

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