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NATURE BEHAVIOR IN STOCHASTIC EXTREME FINDING METHODS

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Abstract: *This paper shows a huge potential of the nature behavior in stochastic function for localization its extreme points. Paper contains a small introduction to using nature phenomenon in multidimensional extreme finding algorithms. Next there were test the beta version of the new custom algorithm for extreme localization based on nature manners. The basic principles are showing in 2- and 3-dimension space and the tests are display in 20-dimension space.*
Key words:*extreme localization, multidimensional function, optimization*

1. INTRODUCTION

The World contains many problems which will be represented by multidimensional function. Solution of the function is solution of specific problem. Stochastic finding function used function of fitness. The fitness is assessment of quality. It is necessary to find this extreme point with the best or the worst fitness of tested function. These points are extreme values. Stochastic methods based on fitness function often used searching methods based on nature behavior or specific natural phenomenon.

As an example might be used SOMA; the SOMA might be presented as a behavior of animal which would survive on desert. Next possible algorithms will be Particle swarm which is based on behavior of flock of birds/bats/honeybee/etc.

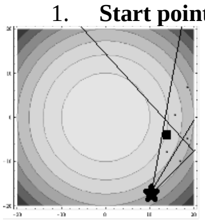
The main purpose of this paper is present possibilities of usage pure natural process for designed extreme finding algorithm.

2. BLIND SHOOTING ALGORITHM

The algorithm is based on easy principle of shooting with 0m visibility. Firstly, there is a starting point and vector; center point for shooting. Secondly, there is a parameter which represented dispersion of shooting (angle of shooting) and number of shoots in specific n-Dimension cone**.** Next parameters represent shooting range; the first is minimal range, second is maximal range. The last package of parameters represented stopping parameters and add stochastic part to this algorithm; probability of movement to worse fitness.

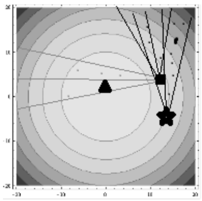
Each phases of algorithm are show bellow. Testing function: Dejong1st; 3-dimension space (2D cut for pictures); blocked stochastic part of algorithm.

1. **Start point**



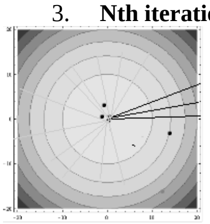
Star point – starting
Black cone – searching cone in 2D space (ricochet on boundaries)
Black points – testing points inside the cone
Black square point – Best fitness point of iteration(if stochastic part is blocked, new starting point).Vector(direction) between blue and red point – new center point of shooting cone for next generation

2. **Nth iteration**



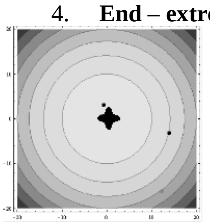
New position from square point was not found a better fitness. Algorithm adds random number to starting angle; from -180 to 180 degree.
One of possible positions after “rotation of shooting cone” is represented by grey lines and triagle points. This rotation was successful and produces new best fitness on the red point inside the gray cone.

3. **Nth iteration(final point)**



The search algorithm is nearly extreme point. There were many of rotation but function is not being able to found a better fitness. Next, there was an exceeding of parameter which represented maximal number of rotation.
Next algorithm refines range of shooting. The search function tries found better fitness. The function end after exceeding maximal same position value; user defined.

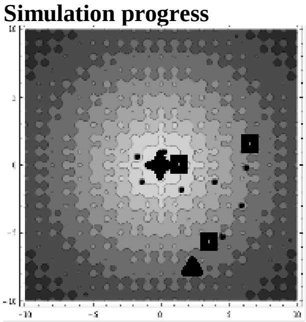
4. **End – extreme point**



End of algorithm. The gray point is starting point of algorithm. Black points represented simulation progress; the best fitness in each iteration. Blackstar is found extreme point of testing function.

The phases of algorithm which use stochastic part are show bellow. Testing function: Ackley; 3-dimension space (2D cut for picture).

Simulation progress



The simulation is same than in non-stochastic part. The triagle point is the starting point. The black points show simulation progress. The black star is found global extreme of testing function.
The square points represented “bad best” (ejected best fitness points). This ejection was in relationship with stochastic part of algorithm. It secures local extreme dead-lock proof.

3. SCHEMA

This part includes basic schema of using algorithm. The schema is on Fig. 1. The search algorithm was created as a parallel; this solution could better use computing capacity of the modern computer systems. There was only one parallel section, which calculates fitness value for each testing point in the iteration. Next, there is thread join operation, which synchronize separated operation. Acceptation of best fitness is in relationship with stochastic part of method.
The breaking point for ending calculation is exceeded of user specified number of rotation in one tested point. The second breaking method is if number of iteration exceeding 10 000 times number of dimensions. This multiplier might be specifying by user. This specific value is using only in tests; it reduce precision, but time reduction is enormous.

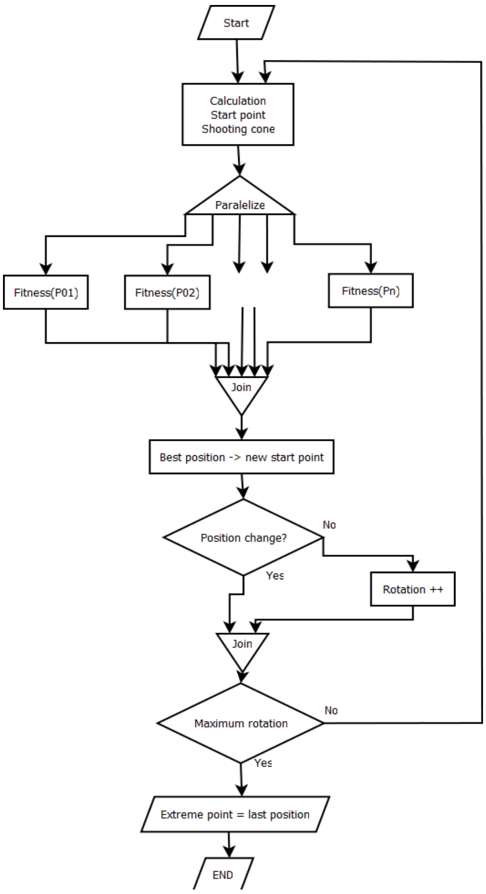


Fig. 1. Basic schema of created algorithm

4. TESTING RESULTS

These 3D tests were realized in Wolfram Mathematica 7 environment.

Start point	[-7.70071 ; -9.02031]
Start value(fitness)	-140.667
Number of iteration	131
Number of fitness calculation	4 250
Found extreme position	[6.833×10^{-13} ; 4.050×10^{-13}]
Found extreme value(fitness)	-6.31044×10^{-25}
Known extreme position	[0 ; 0]
Known extreme value(fitness)	0

Tab. 1. DeJong1st 3D testing result

Start point(the blue point)	[3.72643 ; -9.5665]
Start value(fitness)	-16943.9
Number of iteration	102
Number of fitness calculation	3 366
Found extreme position	[1.60697×10^{-6} ; -1.74361×10^{-6}]
Found extreme value(fitness)	-2.51541×10^{-23}
Known extreme position	[5.75571×10^{-9};1.03158×10^{-8}]
Known extreme value(fitness)	-2.37464×10^{-32}

Tab. 2. DeJong4st 3D testing result

Start point(the blue point)	[-5.08967 ; -6.12683]
Start value(fitness)	1.15253
Number of iteration	36
Number of fitness calculation	1 393
Found extreme position	[-6.28636 ; -4.44736]
Found extreme value(fitness)	2.01481
Known extreme position	[3.14316 ; -1.57772×10^{-30}]
Known extreme value(fitness)	2.00247

Tab. 3. Griewangk 3D testing result

Start point(the blue point)	[-0.421008 ; -7.2625]
Start value(fitness)	-14.9501
Number of iteration	182
Number of fitness calculation	5 780
Found extreme position	[8.164×10^{-15} ; -7.770×10^{-16}]
Found extreme value(fitness)	$- 2.13163\times10^{-14}$
Known extreme position	[-1.704×10^{-16} ; -1.764×10^{-16}]
Known extreme value(fitness)	0

Tab. 4. Ackley 3D testing result

5. CONCLUSION

This paper is showing extraordinary usage of nature phenomenon in the extreme finding operations. Classical methods for extreme finding are based on the gradient methods; these methods are very limited by multiextreme function and for modern application could not be used. Inspiration from life will be next evolution step in extreme finding methods.

Showed result represented behavior of extreme finding method based on “the life”. Visualization is created for 3D space. Created algorithm might be used on single or multi extreme function. Progress displayed on these reports illustrates progress of using “**Blind shooting algorithm**”.

6. ACKNOWLEDGEMENTS

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7. REFERENCES

Zelinka, Ivan,.Aplikaceuměléinteligence. *Zlín : TBU in Zlin, 2010. ISBN 978-80-7318-898-6*

Zelinka, Ivan,.Evolučnívýpočetnítechniky : principy a aplikace *Praha : BEN - technickáliteratura, 2009. ISBN 978-80-7300-218-3*