

Comparison of methods for start points initializing of a non-parametric optimization algorithm

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Abstract. The problem of global optimization arises in various fields of science and technology, and several different ways of solving it have been proposed. The results of the study of the effectiveness of the non-parametric global optimization algorithm are presented. A comparative analysis of this algorithm is presented. performance analysis of the algorithm based on the Ackley, Rastrigin, Shekel, Griewank and Rosenbrock function. In addition, studies were carried out for the three initial points of the distribution algorithms: the sequence LP τ , the sequence UDC, the uniform random distribution. thus, the best way to initialize the initial points of the non-parametric optimization algorithm on these test functions was identified. According to the research results, the effective parameters of the genetic algorithm were established.

1. Introduction

The nonparametric global optimization algorithm [1] differs from the others in that it is the most universal global optimization algorithm. So, it doesn't matter for the algorithm what the object of optimization is and how complex the function is, which describes the object. The object has input and output parameters. We must find an extremum by certain criteria. The parameters of this algorithm are of a high value in order to reach the extremum more efficiently. The research was conducted on Ackley, Rastrigin, Shekel, Griewank and Rosenbrock function [2].

LP τ sequence [3], UDC sequence, uniform random scatter are very interesting and effective scatter algorithms of initial points. Recent research in this area has been carried out in works [4]. These studies were applied to specific practical problems. The goal was not to average these parameters, but to test a complex type of a test function on a large number of practical tasks [5]. LP τ sequences is the algorithm of scattering of points based on the Marshal's matrix of irreducible polynomials. UDC sequence is an algorithm of absolutely uniform distribution of points across all coordinates in multidimensional space [6, 7] regardless of the number of scattered points [8, 9]. Uniform random variation is a stochastic algorithm of scatter of points using a normal distribution (RND).

The paper uses the best parameters for the nonparametric global optimization algorithm:

- The Nuclear function is hyperbolic with the parameter $Q=4$.
- Parameter $\gamma=2$.
- Parameter $P=10$.

2. Experimental study

Figure 1 shows the flowchart of the nonparametric optimization algorithm [1].

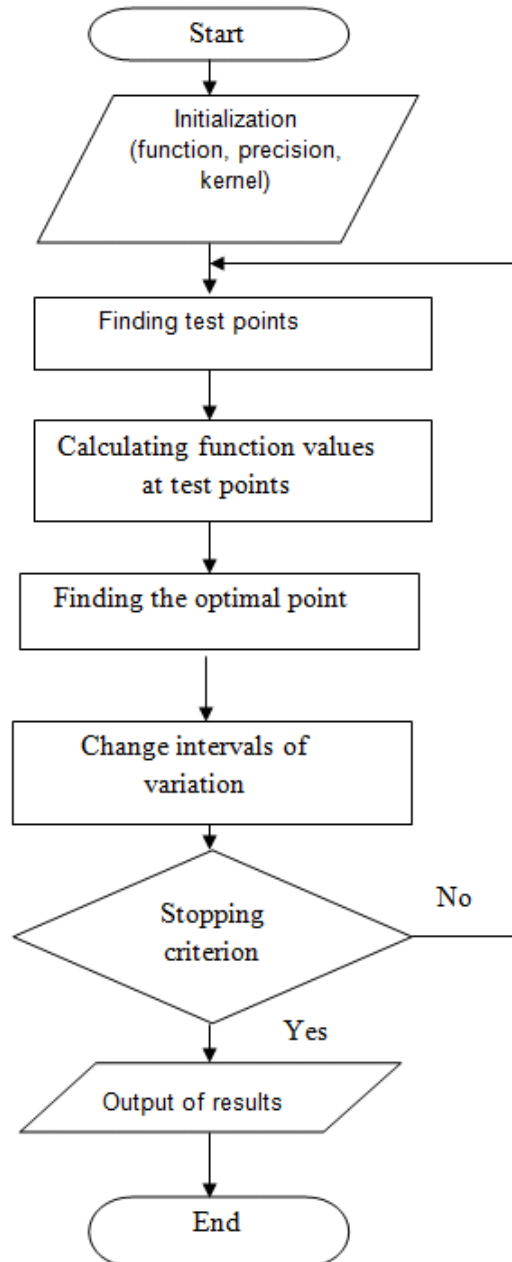


Figure 1. Flowchart of a nonparametric optimization algorithm.

The optimal, in absolute value, parameters of the nonparametric algorithm (N – the number of initial scattered points, IM - the Initialization method, e – accuracy of finding the extremum, $F1(x)$, $F2(x)$ – test functions, Steps – steps of the algorithm to find the extremum with a given accuracy – e , RES , % is the percentage of finding the extremum at a given number of initial points) were determined, for each test function optimized for each point of view (Table 1).

Researches were conducted on test functions: Ackley, Rastrigin, Shekel and Griewank functions. The number of re-runs of the algorithm is 100.

Table 1. Choosing the most effective initialization method.

| N | SI | e=0,01 | | | | e=0,0001 | | | |
|-----|-----------|--------|--------|-------|--------|----------|--------|-------|--------|
| | | F1(x) | | F2(x) | | F1(x) | | F2(x) | |
| | | Steps | Res, % | Steps | Res, % | Steps | Res, % | Steps | Res, % |
| 10 | LP τ | 14 | 0 | 19 | 100 | 32 | 0 | 34 | 100 |
| | RND | 19 | 62 | 20 | 91 | 29 | 35 | 29 | 94 |
| | UDC | 37 | 98 | 32 | 86 | 43 | 58 | 38 | 100 |
| 20 | LP τ | 7 | 0 | 11 | 100 | 7 | 0 | 8 | 0 |
| | RND | 16 | 72 | 15 | 92 | 22 | 37 | 22 | 100 |
| | UDC | 17 | 100 | 16 | 92 | 34 | 56 | 22 | 100 |
| 30 | LP τ | 10 | 100 | 7 | 100 | 9 | 100 | 8 | 100 |
| | RND | 13 | 70 | 12 | 100 | 17 | 54 | 18 | 94 |
| | UDC | 12 | 100 | 12 | 100 | 22 | 68 | 20 | 100 |
| 40 | LP τ | 8 | 100 | 7 | 100 | 9 | 100 | 8 | 100 |
| | RND | 11 | 78 | 1 | 100 | 17 | 57 | 16 | 100 |
| | UDC | 10 | 100 | 12 | 94 | 16 | 70 | 15 | 100 |
| 50 | LP τ | 8 | 100 | 7 | 100 | 9 | 100 | 20 | 100 |
| | RND | 10 | 82 | 10 | 97 | 16 | 54 | 15 | 100 |
| | UDC | 10 | 100 | 10 | 100 | 15 | 76 | 14 | 100 |
| 60 | LP τ | 8 | 100 | 7 | 100 | 9 | 100 | 21 | 100 |
| | RND | 10 | 85 | 10 | 100 | 15 | 60 | 14 | 94 |
| | UDC | 9 | 100 | 10 | 96 | 14 | 72 | 14 | 100 |
| 70 | LP τ | 8 | 100 | 7 | 100 | 9 | 100 | 19 | 100 |
| | RND | 10 | 90 | 10 | 98 | 15 | 54 | 14 | 100 |
| | UDC | 9 | 100 | 10 | 92 | 14 | 80 | 14 | 100 |
| 80 | LP τ | 8 | 100 | 7 | 100 | 19 | 100 | 19 | 100 |
| | RND | 10 | 97 | 9 | 100 | 15 | 52 | 14 | 100 |
| | UDC | 9 | 100 | 9 | 100 | 14 | 85 | 13 | 100 |
| 90 | LP τ | 8 | 100 | 7 | 100 | 19 | 100 | 20 | 100 |
| | RND | 9 | 95 | 9 | 100 | 13 | 78 | 14 | 100 |
| | UDC | 8 | 100 | 8 | 100 | 13 | 94 | 13 | 100 |
| 100 | LP τ | 6 | 100 | 6 | 100 | 15 | 100 | 15 | 100 |
| | RND | 9 | 98 | 9 | 100 | 13 | 65 | 14 | 100 |
| | UDC | 8 | 100 | 8 | 100 | 13 | 96 | 12 | 100 |

The experiments were carried out with an accuracy of 0.0001. The dependence of the algorithm steps on the number of initial points and the dependence of the percentage of finding the extremum on the number of initial points are studied using LP τ spread, UDC spread and uniform scattering and random variation (RND).

Dependence of algorithm steps on the number of starting points is presented in Figure 2.

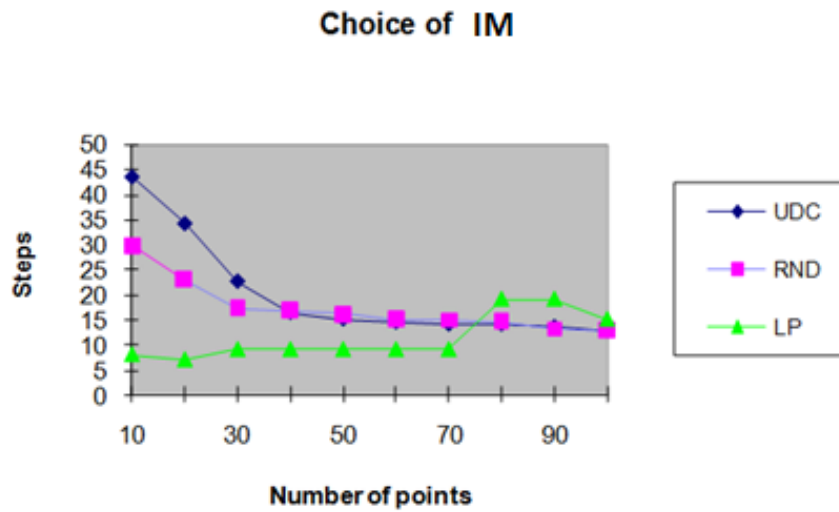


Figure 2. Dependence of algorithm steps on the number of starting points.

Dependence of the percentage of finding the extremum on the number of starting points is presented in Figure 3.

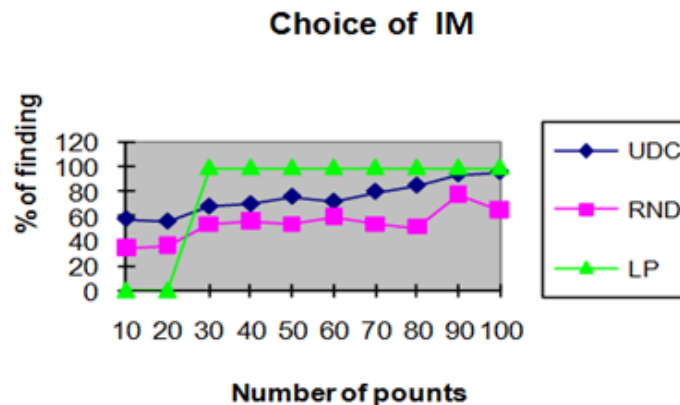


Figure 3. Dependence of the percentage of finding the extremum on the number of starting points.

3. Results

According to table 1 and figures 1 and 2 we can say that the best way of initialization is based on the $LP\tau$ sequence both in terms of convergence and in terms of efficiency. Considering convergence initialization method based on UDC scatter is worse than initialization method based on uniform random spread only when the number of points is less than 40. In all other cases in terms of convergence and in all cases in terms of efficiency, the initialization method based on the UDC spread exceeds the initialization method based on a uniform random spread, but does not exceed the initialization method based on the $LP\tau$ spread.

In the course of the work done, the $LP\tau$ -sequence generator was implemented; qualitative comparisons of the methods of scattering points were conducted. Initialization methods for starting points have been implemented. A non-parametric optimization algorithm was implemented; various initialization methods were compared using a non-parametric optimization algorithm, which showed

the best initialization method, that is LP τ scatter, UDC scatter was worse and uniform random scatter was the worst of all.

4. Conclusion

The nonparametric algorithm of global optimization was analyzed. The research was conducted on Ackley, Rastrigin, Shekel, Griewank and Rosenbrock functions. The studies were carried out for three algorithms of initial point spread: LP τ sequence, UDC sequence, uniform random spread.

As a result of researches the best way of initialization of initial points was revealed. The dependence of the algorithm steps on the number of initial points were studied as well as the dependence of the percentage of finding the extremum on the number of initial points.

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