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Modification Of Species-Based Differential Evolution For Multimodal Optimization

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Abstract. At this time optimization has an important role in various fields as well as between other operational research, industry, finance and management. Optimization problem is the problem of maximizing or minimizing a function of one variable or many variables, which include unimodal and multimodal functions. Differential Evolution (DE), is a random search technique using vectors as an alternative solution in the search for the optimum. To localize all local maximum and minimum on multimodal function, this function can be divided into several domain of fitness using niching method. Species-based niching method is one of method that build sub-populations or species in the domain functions. This paper describes the modification of species-based previously to reduce the computational complexity and run more efficiently. The results of the test functions show species-based modifications able to locate all the local optima in once run the program.

INTRODUCTION

At this time optimization has an important role in various fields of operational research, industry, finance and management. Optimization problem is a problem of maximizing or minimizing a function of one variable or multiple variables, functions examined included unimodal and multimodal function. In searching for the optimum solution can be done by calculus, numerical and random value (random search).

Search the optimum solution by using basic calculus and numerical methods must meet certain requirements. A search solution by using basic calculus method requires an objective function that is continuous or differentiable and has a solution or initial guesses. Numerical methods can not be used directly to search for the optimum solution of an objective function. However the optimum solution can be obtained by finding the roots of the first derivative of the objective function numerically. This means that the use of numerical methods to find the optimum solution also requires the presence of the first derivative of the objective function. Yet in reality often encountered problems with the optimization objective function is discrete and not continuous, not differentiable, has a gradient which fluctuate very quickly, and does not have the guesses/early solution [8].

In this discussion we utilize Differential Evolution (DE), the method is to run a random search techniques using vector as an alternative solution in the search for the optimum. DE is one of the evolutionary algorithm has a performance as good as that of other evolutionary algorithms such as genetic algorithm (GA) [2,3,4]. DE was first introduced by Ken Price's and Rainer storn in 1994 [4], excess DE is the evolution experienced by each individual in a population where differentiation and crossovers occur sequentially in each individual randomly selected from the population at any time. Crossover parameters modified to determine the effect on the computing process. Results of the testing showed crossover parameters which are both used in the differential evolution for optimization problems [3]. In one population vector values to which every individual is distributed randomly will turn into a vector value towards the best value that ultimately becomes the maximum and minimum solution to the function. Although it may seem simple DE to localize the global optimum very fast and accurate [2,8].

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RESEARCH METHODS

Differential Evolution

Differential Evolution (DE) is a method developed by Kenneth Price and published in October 1994 in the magazine Dr. Dobb's Journal (Price et al., 2005). This method is a mathematical function of multidimensional optimization method and included in the group of evolutionary algorithm. The emergence of DE method originates from the business Chebychev polynomial fitting solving problems and generating ideas of using the difference vector to randomize the vector population. Then along with the development, in ICEO (International Contest on Evolutionary Optimization) first, DE becomes one of the best and genetic algorithm can find the global optimum multidimensional (ie showing more than one optimum value) with a good probability [3,4].

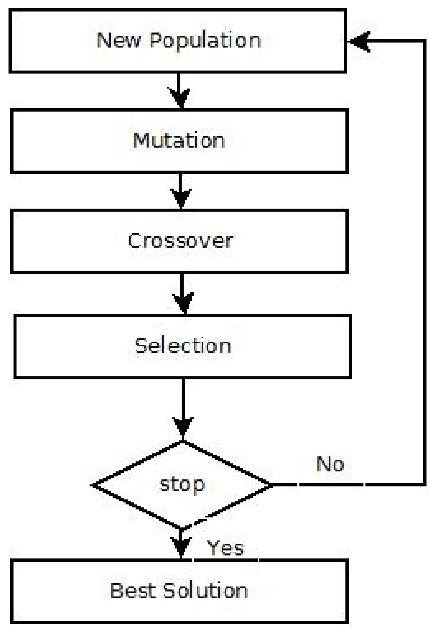

Figure 1. Flowchart for differential evolution

The initial step of this method is the initialization vector generated randomly in area functions.

$$x_{i,j} = x_{i,j_{\min}} + rand(0,1)(x_{i,j_{\max}} - x_{i,j_{\min}}) \quad (1)$$

where j=1,2,..,D (dimensional vector) dan i=1,2,…,NP (the number of vectors in the population), D is the dimension of a vector, NP is a lot of vectors in a population. Area boundary function of each component of the vector can be written $min<x_j<max$, where j=1,2,…,D. Once initialized, DE will mutate and me-recombination initial population to produce new populations.

$$\vec{v}_{i,g} = \vec{x}_{r0,g} + F(\vec{x}_{r1,g} - \vec{x}_{r2,g}) \quad (2)$$

where $\vec{v}_{i,g}$ is mutant vector, g is the vector generation in the process of mutation. The scale factor, $F \in (0,1)$ is a positive real number that controls the development of population changes generated by two vectors are randomly selected from the population. *r0, r2* and *r3* is the index number to generate a random vector of the population. To complete the search strategy differential mutation, DE also employs a crossover.

$$\vec{u}_{i,g} = \begin{cases} \vec{v}_{i,g} \; if\,(rand\ (0,1) \le CR) \\ \vec{x}_i \; otherwise \end{cases} \quad (3)$$

From the equation above, *rand* (0,1) is a random number. *CR* is a constant crossover models specified by the manufacturer. If the random value that appears smaller than *CR* parameters it will be a new vector will appear from the results of the mutation, otherwise it will use a long vector, then in this optimization process prior to the transfer must meet the requirements of crossover parameters. Results of the crossover will be tested with the results of the selection function

Species-Based Differential Evolution

Species-based is one of the methods niching used in multimodal optimization. This method of forming a lot of population in the area function by maintaining the distance (euclidean distance) in the placement of its center point [2,4,5,6]. Each population has a radius (*r*) between the vectors and the population center point. The central point is also called the seed species. Here is the algorithm of formation of species in a population:

1. Spread a random vector in the function area.
2. Sorting each function value of all existing vector, the value of the vector function at its best it is the focal point of the first population.
3. If *r* is the radius of each population, each located within a radius vector *r* will be the first population of the population.
4. The rest of the vector that is then in sorting like (step 2). Having obtained the best value performed (step 3). It will get the second population. And so on.
5. The process will stop if there is no more vectors to be in sorting, or all vectors have entered into one of the populations.
6. Calculate the number of vectors in the population, if all ideal minimal amount for poses DE (ideal minimal amount adjusted for optimization functions), if not ideal vector generation is carried out randomly in a radius populsi.
7. All the population will make the process of DE, until every population converges.
8. Stop if it is found that the criteria chill.

9.

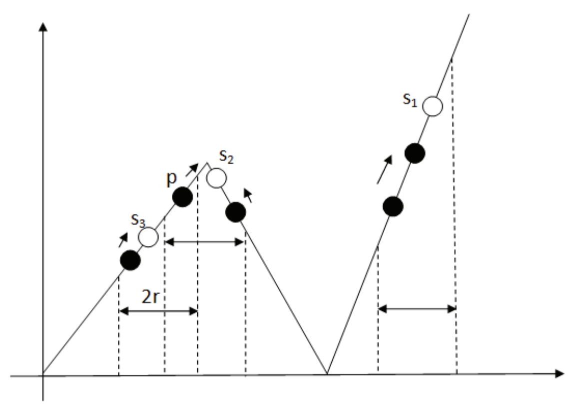

Figure 2. Illustrution for Species-Based

In this illustration explained that *s1*, *s2* and *s3* is a vector that is the center of population. Being p are vectors in the population. The number of vertices in the population can be sure there will be the same as the spread randomly and the proximity of each vector to the center point. Then it could be one of the vectors will get less than ideal vector to make the process of differential evolution [3].

Modification Species-Based Differential Evolution

Development is done in a species-based so that each population has a step formation processes more efficient, while its purpose is:

1. To avoid sorting repeatedly to seek seed species in optimization.

2. In order number of the vector in the population has the same ideal amount for the differential evolution.
3. In order to more evenly spread of seed species to reach all the local optima.

Fundamental changes in the algorithm is in the formation of seed species. Furthermore, I call the seed species featured vector which is the vector that will be the center of change, steps are :

1. Establish a featured vectors first. Formation featured vector is to be raised for the first time, in contrast with the first algorithm that was formed from the best result sorting vectors that have been generated at random. Vector seeded first at the center of an interval function,

$$\vec{x}_{i=1} = \frac{(x_{j_{\max}} - x_{j_{\min}})}{2} \tag{5}$$

2. Establish a featured vectors of the 2nd, 3rd and so on. In this algorithm we set the minimum distance between vectors featured in accordance with the interests and shape of the optimization function. Vector seeded become a reference for superior vector-2 randomly generated, vector seeded 1 and 2 become a reference for vector-3 seed. This process continues until This process continues until certain criteria. If the minimum distance is not met, then the vector randomly generated vectors not be featured. If we generate 100 random vectors could be a featured vectors which occurred less than 100.

$$\vec{x}_p^{\,*} = rand(0,1).(x_{j_{\max}} - x_{j_{\min}}) + x_{j_{\min}} \tag{6}$$

$p = 1,2,...,n$ (number of trials)

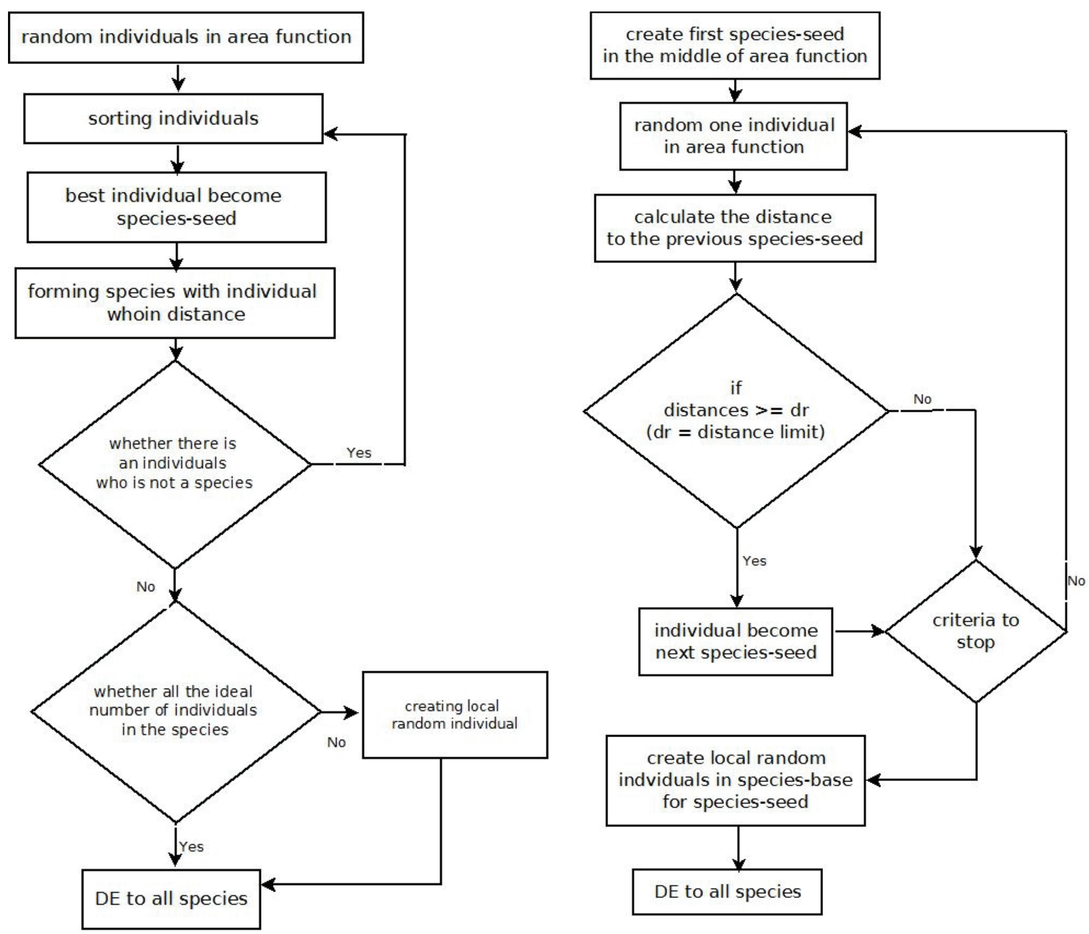

Figure 3. (a) Species Based Scheme, (b) Modification Species-Based Scheme

$$dist(\vec{x}_i, \vec{x}_p^*) = \sqrt{\sum_{i=1}^{NP} (x_{i,j} - x_{p,j}^*)^2} \quad (7)$$

$$if\ dist(\vec{x}_i, \vec{x}_p^*) \geq dr\ then \quad \vec{x}_{i+1} = \vec{x}_p^* \quad (8)$$

where, dr is the amount of distance between vectors

$\vec{x}^*$ is randomly generated vectors, i=1,2,…,NP_{seed} (the amount of seed vectors),
j=1,2,…,D (dimensional vector), $dist$ is the distance between two vectors featured,

RESULT AND ANALYSIS

Test Functions 1.

$$f(x) = 10 + x^2 - 10\cos(2\pi x) \qquad f'(x) = 2x + 20\sin(2\pi x) \quad (9)$$

where $0 \leq x \leq 2$, the radius of the species r = 0.25, in five attempts, the amount of the distribution of 500 vectors, result:

Table 1. Local Maximum in Function 1

No	*x*	*f(x)*	*f'(x)*
1	-0.01744	1.00545	0.003765984
2	3.12412	0.140521	0.000695388
3	-2.11183	3.73344	0.013344813
4	2.07715	0.270779	-0.000902432
5	1.03009	0.521781	-0.004350369
6	-3.15903	7.1942	0.02635617
7	-1.06466	1.93747	0.008868194

Table 2. Local Minimum in Function 1

No	*x*	*f(x)*	*f'(x)*
1	-0.54	-1.4	0.008352695
2	3.648	-0.1	0.000571902
3	0.506	-0.72	0.003002375
4	-3.68	-9.99	0.050191526
5	-1.59	-2.69	0.006167203
6	1.554	-0.38	0.001783059
7	2.601	-0.2	-0.000548008
8	-2.64	-5.18	-0.018755572

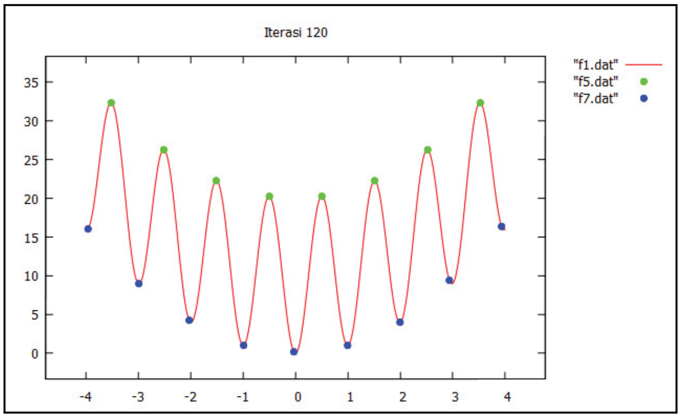

Figure 4. Local optima position Function 1

Test Functions 2, *Himmelblau Function* [4].

$$f(x,y) = 200 - (x^2 + y - 11)^2 - (x + y^2 - 7)^2 \quad (10)$$

$$\frac{\partial f}{\partial x} = 4x(x^2 + y - 11) - 2(x + y^2 - 7) \qquad \frac{\partial f}{\partial y} = 2(x^2 + y - 11) - 4y(x + y^2 - 7) \quad (11)$$

where -6≤x,y≤6, fingers in species r = 2, in five attempts, the amount of the distribution in 2000 vector, we have result:

Table 3. Local Maximum Functions 2

x	*y*	*f(x,y)*	∂f/∂x	∂f/∂y
3.58443	-1.84813	200	-0.000149788	9.03188E-05
3	2	200	0	0
-2.8051	3.13131	200	0.000127537	0.000205066
-3.7793	-3.28319	200	-0.000142705	0.000360865

Table 4. Local Manimum Functions 2

x	*y*	*f(x,y)*	∂f/∂x	∂f/∂y
-0.2708	-0.923039	18.3835	-2.0461E-05	-9.43225E-06

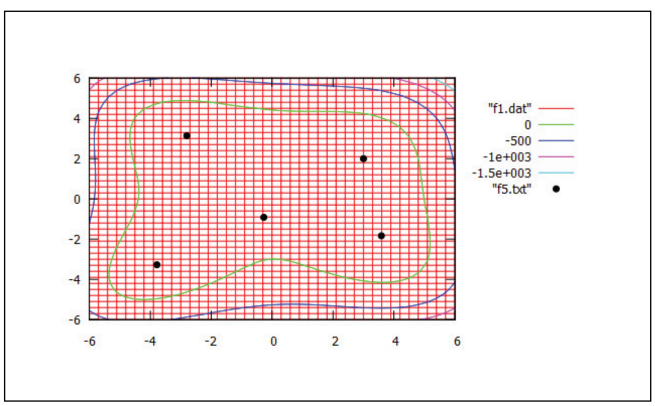

Figure 5. The position of local optima Function 2

Test Functions 3, *Rastrigin's Function* [10].

$$f(\vec{x}) = 10D + \sum_{j=1}^{D}[x_j^2 - 10\cos(2\pi x_j)] \quad (12)$$

$$\frac{\partial f}{\partial x_j} = 2x_j + 20\pi \sin(2\pi x_j) \quad (13)$$

dimana:

$-1 \le x_j \le 1$ $F = 0.5$ $CR = 0.7$ $Population = 50$ $delta = 0.0001$

radius in the species = 0.5 , the distance between vectors seed=0.15

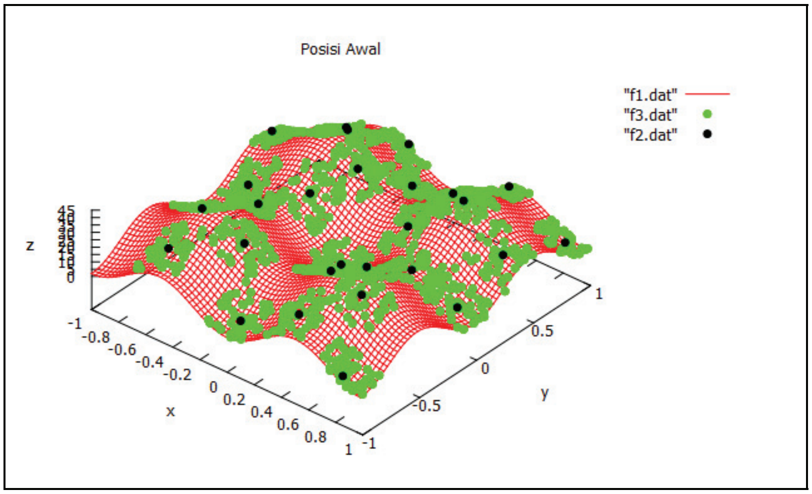

Figure 6. The initial position of the vector in *Rastrigin's Function*

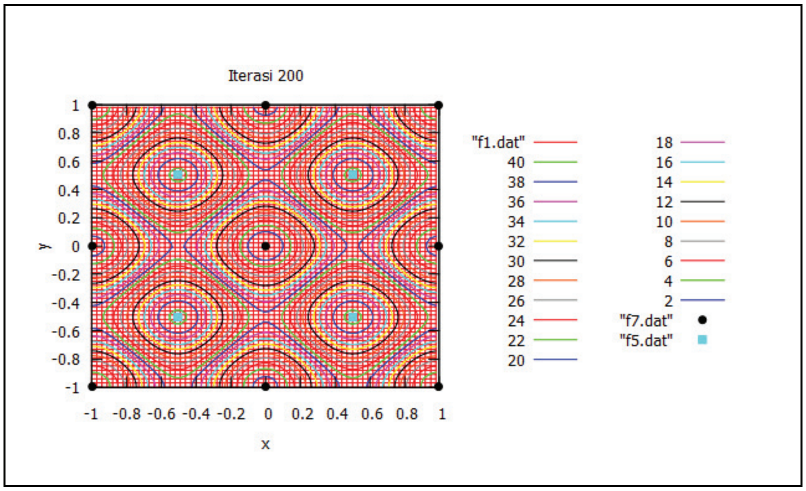

Figure 7. Visualization and position of optima in contour *Rastrigin's Function*

Table 5. Local maximum in *Rastrigin's Function*, D=2

x1	*x2*	*f*(***x***)	∂*f*/∂*x1*	∂*f*/∂*x2*
0.5028	-0.5028	40.503	0.001386247	-0.001386247
0.5028	0.5028	40.503	0.001386247	0.001386247
-0.5028	0.5028	40.503	-0.001386247	0.001386247
-0.5028	-0.5028	40.503	-0.001386247	-0.001386247

Table 6. Local minimum in *Rastrigin's Function*, D=2

x1	*x2*	*f*(***x***)	∂*f*/∂*x1*	∂*f*/∂*x2*
5.55E-11	6.53E-10	0	2.19993E-08	2.58839E-07
8.79E-10	0.995458	0.996	3.48422E-07	-7.97337E-05
0.995458	-1.54E-09	0.996	-7.97337E-05	-6.10431E-07
0.995458	0.995458	1.9919	-7.97337E-05	-7.97337E-05
-0.99546	-0.99546	1.9919	7.97337E-05	7.97337E-05
-1.45E-10	-0.99546	0.996	-5.74757E-08	7.97337E-05
-0.99546	2.44E-09	0.996	7.97337E-05	9.67177E-07
0.995458	-0.99546	1.9919	-7.97337E-05	7.97337E-05
-0.99546	0.995458	1.9919	7.97337E-05	-7.97337E-05

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