Accelerating Differential Evolution Using Multiple Exponential Cauchy Mutation

Tae Jong Choi
Sungkyunkwan University
Suwon, Republic of Korea
gry17@skku.edu

Chang Wook Ahn*
Gwangju Institute of Science and Technology
Gwangju, Republic of Korea
cwan@gist.ac.kr

ABSTRACT

Differential Evolution (DE) is a robust optimization algorithm, but it suffers from the stagnation problem in which individuals may not escape from a local optimum. In this article, we proposed a new Cauchy mutation using multiple exponential recombination, self-adaptive parameter control, and linear failure threshold reduction. The proposed method is a simple yet efficient to mitigate the stagnation problem, and it can improve the convergence speed of DE. Our experimental results show that the proposed method can find more accurate solutions to complicated problems.

CCS CONCEPTS

• **Theory of computation → Evolutionary algorithms**; **Evolutionary algorithms**; **Bio-inspired optimization**;

KEYWORDS

Artificial Intelligence, Evolutionary Computing and Genetic Algorithms, Global Optimization

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1 INTRODUCTION

Differential Evolution (DE) [5] is an evolutionary algorithm that performs well in finding the optimum in real-valued continuous functions. However, DE, like other population-based metaheuristic algorithms, suffers from the stagnation problem in which individuals may not escape from a local optimum. Many researchers have attempted to solve this problem by proposing various techniques, and one of these techniques is to utilize the Cauchy distribution. The Cauchy distribution can generate a large jump with its heavy tail, and this can allow individuals to move far away from their current locations. Ali et al. proposed MDE [1] that applies the Cauchy distribution to the individuals which fail to evolve sequentially to make them move other locations.

In this article, we propose a new Cauchy mutation that can find more accurate solutions to complicated problems than original the Cauchy mutation. The proposed method uses the p-best individual instead of the best individual to reduce greediness, thereby preventing the premature convergence problem. And, the proposed method uses the multiple exponential recombination [4] instead of the binomial crossover to prevent building blocks from collapsing, thus ensuring robust performance in inseparable problems. We also use a self-adaptive technique [3] to adjust the recombination rate for the Cauchy mutation automatically. Finally, it applies the linear failure threshold reduction technique [6] to control the probability of conducting the Cauchy mutation appropriately according to the search step.

2 MULTIPLE EXPONENTIAL CAUCHY MUTATION

Although MDE shows better performance than standard DE, it has several fatal problems. First, MDE only uses the best individual information when conducting the Cauchy Mutation, and high greediness can cause the premature convergence or the lack of population diversity. Second, MDE uses a fixed recombination rate, and a fixed parameter may not be able to handle various problems effectively. Finally, MDE uses a fixed failure threshold, and again, it may not reflect the characteristics of various problems well. In this article, we propose Multiple Exponential Cauchy Mutation (MECM) to solve these problems.

2.1 P-best and Multiple Exponential Methods

Algorithm 1 Multiple Exponential Cauchy Mutation

$E_m = T \cdot R_i^G,\ E_s = T \cdot (1 - R_i^G)$
$CR_m = E_m/(E_m + 1),\ CR_s = E_s/(E_s + 1)$
$n = rand[1, D],\ M = true$
for $k = 1$ **to** $k = D$ **do**
  $d = n\%D$
  if $M = true$ **then**
    $u_{i,d}^G = x_{p-best,d}^G,\ M = false$
  else
    $u_{i,d}^G = x_{i,d}^G,\ M = true$
  end if
  $n = n + 1$
end for

The proposed method uses the p-best individual selection and the multiple exponential recombination. The p-best individual selection can reduce the greediness of DE significantly by selecting the individual of the upper $p\%$ instead of the best individual. And, the multiple exponential recombination [4] is a new crossover that combines the advantages of the binomial and exponential crossovers,

*The corresponding author

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which can improve the performance of inseparable and higher dimensional problems. Algorithm 1 shows the pseudocode of the proposed algorithm.

2.2 Self-adaptive Recombination Rate

MDE uses a fixed recombination rate (0.9) in the Cauchy mutation. The proposed method uses a self-adaptive technique [3] to automatically tune the recombination rate. Each individual has its own recombination rate, and if the Cauchy mutation is conducted because an individual continuously failed to evolve, a new recombination rate for the individual is assigned as follows.

$$R_i^{G+1} = \begin{cases} rand[0,1] & rand[0,1] \leq \tau \\ R_i^G & \text{otherwise} \end{cases} \tag{1}$$

where R_i^G denotes the recombination rate and τ represents the probability of adjusting the recombination rate.

2.3 Linear Failure Threshold Reduction

The proposed method employs a linear failure threshold reduction technique, which sets the failure threshold to a high value initially and gradually decreases over generations. The reason for such a design is as follows: It is possible to search another space through a general DE mutation and crossover operators, regardless of which individual initially falls into a local optimum, but it is difficult to escape from a local optimum because the population diversity is lowered as the generation passes. The technique that reduces the failure threshold according to generation can be designed in various ways, but in the proposed method, we devise a simple and efficient way by referring to [6]. The new failure threshold for each generation is calculated as follows.

$$FT^G = FT_{max} + \frac{FT_{min} - FT_{max}}{G_{max}} \cdot G \tag{2}$$

3 EXPERIMENTS

We performed experiments on CEC 2017 bound constrained real-parameter benchmark problems [2] to calculate the performance of the proposed method. The comparison algorithms and assigned control parameters are as follows.

1. DE [5], $F = 0.5, CR = 0.9$
2. Cauchy Mutation with DE [1], $F = 0.5, CR = 0.5, FT = 5$
3. MECM with DE, $F = 0.5, CR = 0.5, FT_{max} = 10, FT_{min} = 3$

We performed a total of 100 independent experiments, and Table 1 is summarized the experimental results. The experimental results show that the proposed Cauchy mutation improves performance, especially for solving the complicated problems such as multimodal, hybrid, and composition functions. This performance improvement is possible because it can lower the greediness and efficiently apply the appropriate recombination rate depending on the optimization progress. As a result, we confirmed that the proposed MEMC method could provide a better performance improvement by combining with DE.

Table 1: CEC 2017 benchmark results on 30 dimension

	CM + DE		MECM + DE		DE	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
F_1	**9.47E+00**	**6.79E+00**	1.01E+02	6.08E+01	1.68E+02	8.81E+01
F_2	**1.14E-03**	**6.29E-04**	1.06E+19	5.41E+19	7.96E+26	2.63E+27
F_3	**1.61E+00**	**5.94E-01**	3.41E+04	5.69E+03	4.08E+04	6.24E+03
F_4	**5.04E+01**	**3.30E+01**	8.60E+01	4.13E+00	8.52E+01	2.27E-01
F_5	8.51E+01	2.31E+01	**4.44E+01**	**1.44E+01**	1.70E+02	8.59E+00
F_6	8.95E-02	2.14E-01	**6.90E-13**	**4.43E-13**	1.19E-12	8.75E-13
F_7	**1.30E+02**	**2.79E+01**	1.35E+02	2.70E+01	2.09E+02	1.06E+01
F_8	9.09E+01	2.25E+01	**4.45E+01**	**1.43E+01**	1.72E+02	1.04E+01
F_9	4.95E+02	4.53E+02	1.03E-14	3.28E-14	**6.84E-15**	**2.72E-14**
F_{10}	3.30E+03	5.88E+02	**3.16E+03**	**6.19E+02**	6.63E+03	2.14E+02
F_{11}	1.05E+02	4.87E+01	**4.77E+01**	**2.80E+01**	1.05E+02	2.28E+01
F_{12}	**6.87E+04**	**3.36E+04**	7.34E+05	4.62E+05	5.03E+06	1.69E+06
F_{13}	**1.06E+04**	**1.20E+04**	1.67E+04	7.12E+03	2.33E+04	1.14E+04
F_{14}	1.60E+02	7.10E+01	**1.10E+02**	**1.02E+01**	1.18E+02	1.03E+01
F_{15}	3.28E+03	4.71E+03	**2.67E+02**	**4.43E+01**	3.32E+02	4.58E+01
F_{16}	1.08E+03	2.83E+02	**5.48E+02**	**2.12E+02**	1.03E+03	1.47E+02
F_{17}	4.89E+02	2.25E+02	**6.61E+01**	**4.23E+01**	1.93E+02	2.63E+01
F_{18}	**8.96E+04**	**4.35E+04**	2.22E+05	1.24E+05	5.85E+05	2.12E+05
F_{19}	4.59E+03	6.43E+03	**9.41E+01**	**1.91E+01**	1.18E+02	2.86E+01
F_{20}	4.89E+02	1.91E+02	**7.06E+01**	**6.87E+01**	2.11E+02	4.65E+01
F_{21}	2.93E+02	2.74E+01	**2.46E+02**	**1.23E+01**	3.66E+02	1.08E+01
F_{22}	6.73E+02	1.34E+03	**1.00E+02**	**0.00E+00**	1.00E+02	0.00E+00
F_{23}	4.43E+02	2.74E+01	**3.92E+02**	**1.29E+01**	5.14E+02	9.98E+00
F_{24}	5.02E+02	2.49E+01	**4.66E+02**	**1.52E+01**	5.90E+02	1.04E+01
F_{25}	3.87E+02	1.61E+00	**3.87E+02**	**0.00E+00**	3.87E+02	0.00E+00
F_{26}	2.08E+03	4.26E+02	**1.40E+03**	**1.32E+02**	2.60E+03	1.11E+02
F_{27}	5.35E+02	1.41E+01	**5.02E+02**	**4.80E+00**	5.07E+02	1.01E+01
F_{28}	**3.60E+02**	**6.41E+01**	3.91E+02	3.50E+01	4.02E+02	2.18E+01
F_{29}	9.16E+02	2.19E+02	**5.64E+02**	**8.97E+01**	8.99E+02	7.35E+01
F_{30}	**7.94E+03**	**3.38E+03**	2.56E+04	6.97E+03	4.17E+04	1.25E+04
Rank	2.03		1.50		2.53	

4 CONCLUSION AND FUTURE WORK

In this article, we proposed a simple yet effective new Cauchy mutation that can alleviate the stagnation problem and improve the performance of DE. The proposed Cauchy mutation combines with multiple exponential recombination, self-adaptive parameter control, and linear failure threshold reduction techniques. This reduces the greediness of the algorithm and prevents building blocks from collapsing, ensuring performance in inseparable and higher dimensional problems, finding a flexible recombination rate according to the nature of a problem, and controlling the failure threshold according to the algorithm's progress. The proposed method was evaluated on a total of 30 CEC 2017 benchmark problems, and we confirmed that the proposed method could increase the performance of DE, especially in complicated problems such as multimodal, hybrid, and composition problems. In future work, we will apply and evaluate the proposed algorithm for multimodal and multi-objective problems.

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