Chapter 1

A Cultivated Variant of Differential Evolution Algorithm for Global Optimization

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ABSTRACT

Differential Evolution (DE) algorithm is known as robust, effective and highly efficient for solving the global optimization problems. In this chapter, a modified variant of Differential Evolution (DE) is proposed, named Cultivated Differential Evolution (CuDE) which is different from basic DE in two ways: 1) the selection of the base vector for mutation operation, 2) population generation for the next generation. The performance of the proposed algorithm is validated on a set of eight benchmark problems taken from literature and a real time molecular potential energy problem. The numerical results show that the proposed approach helps in formulating a better trade-off between convergence rate and efficiency. Also, it can be seen that the performance of DE is improved in terms of number of function evaluations, acceleration rate and mean error.

MAIN FOCUS OF THE CHAPTER

The main focus of this chapter is to provide new technique using which maximum exploration and exploitation of the search space can be done. So that, a quality solution without any compromise can be generated at the minimum CPU time. This is done in the present study by taking two phases of the basic DE algorithm into consideration for enhancement: mutation and selection. Mutation is the main phase of basic DE algorithm, in which after rendering the whole search space a mutant vector is generated. That’s why a new technique to maximize the exploitation of the search space and to optimize the solution vector is adapted. Next, in the basic DE algorithm, selection of the candidate solution for the next generation is done by tournament selection process in which the objective function value of the target vector is compared to its corresponding trial vector, generated after the application of mutation and crossover operators respectively and the one having the minimum objective function value will be
served to the population for the next generation. Here, the main problem is the loss of information and computational time. It may happen that a quality candidate solution can be lost in this process. Such as a candidate solution which is left in the previous tournament selection process can be better than the candidate solution produced in the current tournament process, but later it can’t be used as it is lost. So in the current study, information preservation concept is used for escaping from loss of information which is explained in the next section.

**INTRODUCTION**

Evolutionary Algorithm (EA) is a stochastic population-based algorithm and has significant rise in the field for solving multi-objective optimization problems because of the fact that EA deals with a set of solutions more efficiently than classical methods. In the mid-90s, Differential Evolution (DE) is initially proposed by Storn and Price (1997) for optimization problems over continuous spaces as a new addition to EAs. EA works with three operators named selection, crossover and mutation. DE also uses the same operators, but the difference between DE and other EAs is the working of these operators. DE mainly comprises the characteristics of convergence speed, robustness and simple in terms of application. Within a short period of approx. 30 years, DE has been successfully applied in a very simple and efficient way for solving single-objective global optimization problems and in many other application fields such as pattern recognition (Wang, Zhang, & Zhang, 2007), medical science (Plagianakos, Tasoulis, & Vrahatis, 2008), integer programming problems (Zaheer & Pant, 2014), chemical engineering and various science and engineering fields (Ilonen, Kamarainen, & Lampinen, 2003). Also DE has been successfully applied to a wide range of problems including Batch Fermentation Process (Wang & Cheng, 1999), Optimal design of heat exchanges (Babu & Munawar, 2007), synthesis and optimization of heat integrated distillation system (Babu & Singh, 2000), optimization of non-linear chemical process (Angira & Babu, 2005), optimization of process synthesis and design problems (Angira & Babu, 2006), optimization of thermal cracker operation (Babu & Angira, 2001), optimization of water pumping system (Babu & Angira, 2003), dynamic optimization of a continuous polymer reactor (Lee, Han, & Chang, 1999), optimization of low pressure chemical vapour deposition reactors (Lu & Wang, 2001), and recently used for multi-level image thresholding (Ali, Ahn, & Pant, 2014; Ali, Ahn, Pant, & Siarry, 2015) etc.

DE is a simple and efficient search engine which can handle nonlinear, non-differentiable and multimodal objective functions. DE outperforms in terms of convergence rate and robustness over benchmark problems and real life problems. Despite having several attractive features and successful applications to various fields DE is sometimes criticized for its slow convergence rate for computationally expensive functions. By varying the control parameters the convergence rate of DE may be increased, but it should be noted that it does not affect the quality of solution. Generally, in population based search techniques like DE an acceptable trade-off should be maintained between convergence and type of solution, which even if not a global optimal solution should be more satisfactory rather than converging to a suboptimal solution which may not even be a local solution. Several attempts have been made in this direction to fortify DE with suitable mechanisms to improve its performance. Most of the studies involve the tuning or controlling of the parameters of algorithm and improving the mutation, crossover and selection mechanism, some interesting modifications that helped in enhancing the performance of DE include introduction of greedy random strategy for selection of mutant vector (Bergey & Ragsdale, 2005),