Non-Monotone Differential Evolution

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ABSTRACT

The Differential Evolution algorithm uses an elitist selection, constantly pushing the population in a strict downhill search, in an attempt to guarantee the conservation of the best individuals. However, when this operator is combined with an exploitive mutation operator can lead to premature convergence to an undesired region of attraction. To alleviate this problem, we propose the Non-Monotone Differential Evolution algorithm. To this end, we allow the best individual to perform some uphill movements, greatly enhancing the exploration of the search space. This approach further aids algorithm's ability to escape undesired regions of the search space and improves its performance. The proposed approach utilizes already computed pieces of information and does not require extra function evaluations. Experimental results indicate that the proposed approach provides stable and reliable convergence.

Categories and Subject Descriptors

G.1.6 [**Numerical Analysis**]: Optimization—*global optimization, unconstrained optimization*; I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*heuristic methods*

General Terms

Algorithms

Keywords

Evolutionary Algorithms, Differential Evolution, Non-Monotone Differential Evolution, Global Optimization

1. NON-MONOTONE DIFFERENTIAL EVOLUTION (NMDE)

The main features of Differential Evolution (DE) [2] are its simplicity, fastness and robustness. Although various DE mutation operators have been proposed, they have different impact on the exploration of the search space. Additionally, the selection operator, which dictates monotone decrease of the function values, provides an efficient and effective way to ensure that the objective function is reduced sufficiently. However, it has the disadvantage that no information, which might accelerate convergence, is stored and utilized. In extreme cases, an exploitive mutation operator, combined with the elitist selection operator, can lead to premature convergence of the population. The same effect has the poor selection of DE's control parameters. For example, if the mutation rate is too high, much of the search space will be explored, but there is a high possibility of losing promising solutions; the algorithm has difficulty to converge to an optimum due to insufficient exploitation. To alleviate this situation, we propose the Non-Monotone DE (NMDE) selection operator applied on the best individual of each generation, exploiting the accumulated information with regard to the most recent function values of the best individual. To this end, we allow the best individual to perform some uphill movements, i.e. the fitness of the best individual is allowed to increase at some generations.

In this paper, we demonstrate the application of the NMDE operator on the DE/best/1 and the DE/best/2 algorithms [2]. It is evident that when using operators that utilize the best individual as their base vector, the selection of the best individual is crucial to the evolution of the population. We argue that the selection of the best individual must satisfy a non-monotone criterion with respect to the maximum fitness of the M previous best individuals of the population. Parameter M is called the *non-monotone horizon*. More specifically, the best individual must satisfy the following equation:

$$f(u_{g+1}^{\text{best}}) \leqslant \max_{0\leqslant j\leqslant M}\{f(u_{g-j}^{\text{best}})\},$$

where the non-monotone horizon M is a small non-negative integer and u_{g+1}^{best} is the newly assigned best individual. Larger values of M allow better search space exploration. Thus, in difficult multimodal objective functions larger values of M are recommended. On the other hand, objective functions possessing only a few minima can be solved using smaller values of M. A deterministic non-monotone learning strategy of similar conception for neural network training has been proposed in [1].

Furthermore, at the top of Table 1 the algorithmic scheme for the proposed approach is outlined, while at the bottom the **SelectBestIndividual()** procedure exhibits the implementation of the non-monotone criterion. Additionally, in Figure 1 the fitness of the best individual is illustrated for DE/best/1 applied on Levy No. 5 test function with non-monotone horizon $M = 5$. It is clear that although at some generations the fitness of the best individual is allowed to increase, the modified DE algorithm converges to the global minimum of the objective function.

2. EXPERIMENTAL RESULTS

We implemented and tested the proposed NMDE algorithm on a large number of optimization benchmarks. In

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Table 1: NMDE: the proposed approach

```
Begin
  Initialize the population of NP individuals
  Evaluate the fitness of each individual
  Repeat
    For i = 1 to NP Do
      Mutation(x_g^i) → Mutant_g^i
      Recombination(Mutant_g^i) → Trial_g^i
      If f(Trial_g^i) ⩽ f(x_g^i) Then
        accept Trial_g^i for the next generation
      EndIf
      SelectBestIndividual()
    EndFor
  Until the termination criteria are satisfied
End
```

Function SelectBestIndividual()

```
Begin
  If f(u_{g+1}^best) ⩽ max_{0⩽j⩽M}{f(u_{g-j}^best)} Then
    assign u_{g+1}^best as best for the next generation
  EndIf
End
```

this study, due to space limitations, we report experimental results of eight well–known minimization test functions. For each test function and each mutation operator, we have conducted 1000 independent runs and have used the fixed values of $F = 0.5$ and $CR = 0.7$ as the DE mutation and crossover constants respectively.

To evaluate the proposed NMDE, we compared its performance on eight test functions [3]. For each test function we experimented using ten values for the non-monotone horizon, $M = 1, 2, \ldots, 10$. It is evident that, when $M = 1$ only monotone evolution of the best is performed and the algorithm is identical to the original DE/best/num, $num = 1, 2$. Figure 2 illustrates the average function evaluations and the corresponding success rates for the non-monotone DE/best/1 and DE/best/2 algorithms. The experimental results on the eight test functions indicate that the proposed approach exhibits better success rates than the original DE algorithm, at the expense of a slight increase of the average function evaluations required.

To conclude, the proposed approach enhances DE's ability to accurately locate solutions in the search space and to escape undesired regions of attraction, leading in increased success rate. Non-Monotone Differential Evolution performs consistently and reasonably well for different test functions, and potentially, alleviates problems such as the decreased rate of convergence, divergence and premature saturation. Thus, for an unknown optimization problem the application of the non-monotone DE is recommended.

3. REFERENCES

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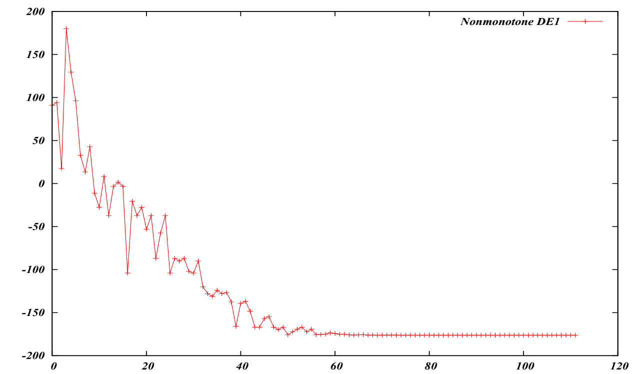

Figure 1: DE/best/1: Fitness value of the best individual (Levy No. 5, non-monotone horizon = 5)

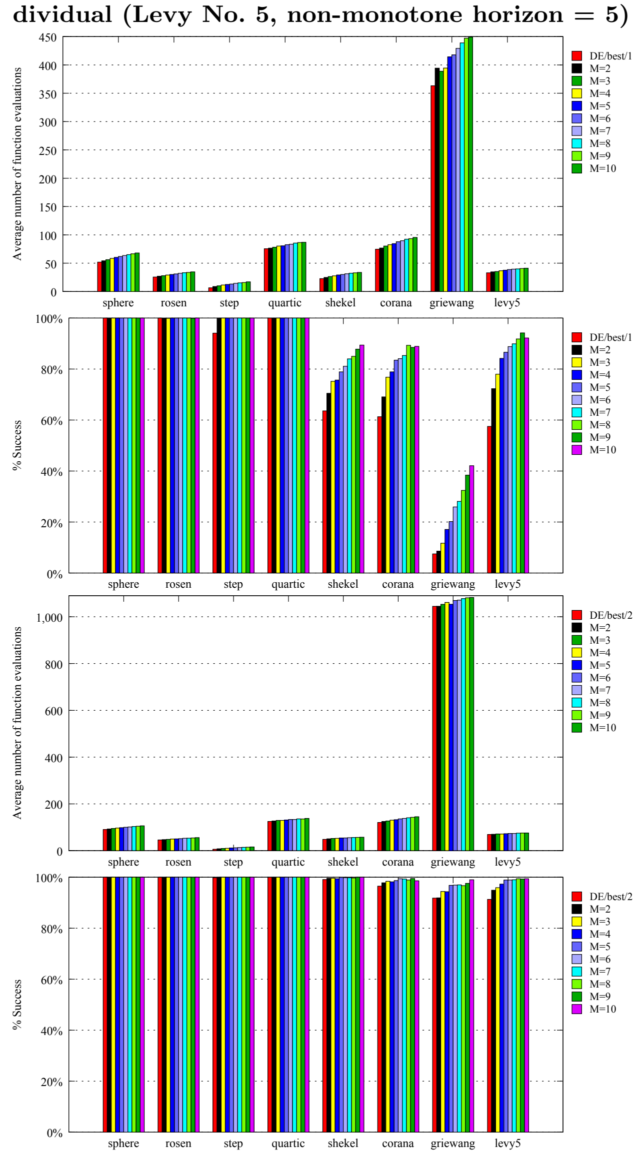

Figure 2: Average number of function evaluations and success percentage for DE/best/1 and DE/best/2 (non-monotone horizon values 1 to 10)